Welfare Effects of Full-Line Forcing Contracts in the U.S. Health Care Market

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Abstract

I study the welfare implications of bundling practices exercised by hospital systems in the negotiation process with insurers. Hospital systems offer full-line forcing contracts to ensure insurers carry all hospital system members in their networks. Such contracts have potential efficiency-inducing and anti-competitive effects from a theoretical standpoint, making welfare implications ambiguous. Using regression analysis, I demonstrate efficiency gains present themselves through their impact on market coverage, but not on premiums. Moreover, hospital systems are unable to use these contracts to gain leverage over their rivals, making anti-competitive effects absent from the picture. To quantify the overall impact on welfare, I estimate structural models of hospital and insurer demand along with a bargaining model, and use the parameter estimates in a counterfactual policy experiment that prohibits such contracts. Results from counterfactual simulations suggest that removal of full-line forcing contracts from the market leads to a $16 billion decline in overall welfare. Consumers are worse off because they face higher premiums in the absence of vertical bundling. Removal of vertical restraints benefits majority of insurers, but many hospitals suffer losses. System hospitals lose the most since they no longer can use bundling to maximize their profits. Individual hospitals also lose as a result of increased competition in the upstream market.

JEL: I11, I13, L14, L42

Keywords: bundling, tying, full-line forcing, bargaining, hospitals, health insurance

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1 Introduction

Bundling arrangements between upstream and downstream firms have been frequently challenged on the grounds that they pose a threat to competition (Hilton (1958)). In particular, two kinds of vertical bundling practices have been subjects of policy debates: tying the sale of a good to the machine that processes it, and full-line forcing (FLF) contracts where the upstream supplier forces the downstream distributor to carry full-line of its products. This paper focuses on the latter, and studies the welfare implications of FLF contracts in the health care industry in the United States.[1] FLF contracts are offered by hospital systems to ensure insurers carry all system member hospitals in their networks.[2] Understanding the welfare impacts of FLF contracts in health care is important, especially given the hospital merger wave of 1990s that resulted in an increase in the number of hospital systems.

In the U.S. health care system, price paid to providers by insurers per unit of care is determined in yearly negotiations. This bargaining process creates incentives for both parties to gain leverage as the total surplus in the market is shared between them based on their bargaining positions. Historically, Health Maintenance Organizations (HMOs) managed to drive hospital prices down as hospitals wanted to be included in their narrow provider networks. Providers' response to the rise of managed care was in the form of horizontal consolidation (Fuchs (1997)). In order to increase their bargaining power, many individual hospitals went through mergers and formed or became members of hospital systems. Since 1994, more than 1000 hospital mergers took place (Gaynor et al. (2015)). Today, among 5534 registered hospitals in the U.S., 3231 are members of hospital systems.[3] As the system hospitals represent a larger proportion of the hospital market every year[4], the FLF contracts they offer are expected to have a substantial impact on welfare.

There is no consensus in the economic theory literature regarding the welfare impacts of vertical bundling arrangements. A large portion of this literature studies the strategic motives for firms to offer bundling contracts, and these motives have varying welfare implications. Among the most popular views are the intents to use vertical bundling as a device to mimic the effects of vertical integration (Burnstein (1960a, 1960b)), extend market power into new markets and exclude or deter entry of rivals (Whinston (1990)), price

[1] Presence of full-line forcing contracts in the health care industry has been documented in Antitrust Health Care Handbook, *American Bar Association*, Third Edition, page 142.

[2] Individual hospitals also can offer FLF contracts by requiring the insurer to carry all of the services offered by that hospital. I do not observe services covered by an insurer at a hospital in my data, hence I focus only on the FLF contracts offered by hospital systems.

[3] Source: American Hospital Association, Fast Facts on U.S. Hospitals, 2018.

[4] System hospitals constituted 56.6% of all registered hospitals in 2016, and this figure increased to 57.5% in 2017 and 58.4% in 2018. Source: American Hospital Association, Fast Facts on U.S. Hospitals, 2016, 2017, 2018.

discriminate (Stigler (1963), Adams and Yellen (1976)), and circumvent price control regulations (Hilton (1958)). Only the first two are relevant in the context of this paper.[5] FLF contracts can be used to imitate the efficiency effects of vertical integration because firms with market power can attain higher profits by selling the bundle at a single price rather than individually pricing their products. Offering discounts -and hence eliminating double marginalization to some extent- is among the upstream firms' motives to make the bundle more attractive to downstream firms. On the other hand, vertical bundling can be used to foreclose competition, gain leverage over rivals (Whinston (1990), Carlton and Waldman (2002)), and restrict their entry (Choi and Stefanadis (2001), Nalebuff (2004)). Since both efficiency-inducing and anti-competitive effects are present from a theoretical standpoint, the overall impact on welfare is ambiguous.

Studying welfare impacts of FLF contracts is, therefore, an empirical question that needs to be addressed based on the implications of these theoretical motives. In vertically-separated markets, these motives translate into three potential effects: leverage, efficiency, and market coverage (Ho et al. (2012b)). In the context of health care, the leverage effect might be present if insurers that accept FLF contracts carry fewer rival hospitals in their networks. This might have an adverse effect on consumer welfare if hospitals unfavorable to consumers are included in an insurer's network at the expense of more desired hospitals. Efficiency gains might realize if hospital systems offer discounts for all-or-nothing contracts, reducing the unit cost for insurers. Insurers who accept FLF contracts can then offer lower premiums if they choose to pass along these savings to their enrollees; or they can expand their market coverage and include a greater number of hospitals in their network for the same cost. Either way, consumer welfare will improve.

I begin my analysis by investigating the presence of these effects in the market for health care. Using regression analysis, I demonstrate that the efficiency effect presents itself through its impact on market coverage. FLF-accepting insurers have larger hospital networks compared to insurers who do not accept FLF contracts, but their premium levels do not differ significantly. Moreover, accepting an FLF contract from a hospital system does not interfere with the inclusion of any category of the rival hospitals in the market. In fact, FLF-accepting insurers include more individual hospitals, non-FLF system hospitals, and rival FLF system hospitals in their networks. Given the absence of the leverage effect along with increased market coverage, one would expect FLF contracts' impact on consumer welfare to be positive. In order to quantify this effect

[5] Price discrimination argument does not apply to the case studied here because prices paid to hospitals by insurers are determined in yearly negotiations (except in Maryland). Hence, if two insurers value a certain hospital differently, the hospital can charge different prices to the two insurers for the same set of services. Hospital prices are controlled only in Maryland; there are no national price control regulations that will drive the results in this paper.

and measure the impact on producer surplus, I estimate a structural model and simulate a counterfactual world where FLF contracts do not exist.

My structural model aims to understand how consumer demand for hospitals and insurers as well as hospital costs are determined. I also estimate a bargaining model to understand how networks are formed as a result of hospital-insurer negotiations. Simulation of the counterfactual world uses all parts of the structural model to predict how all agents in the market would behave under the new scenario. In the counterfactual world, I ban FLF contracts. This implies hospital systems that imposed all their member hospitals on insurers now enter the bargaining game as individual entities. Therefore, there are no vertical restraints imposed by upstream entities, and all the hospitals in the market act individually. Given the new players and results from bargaining estimation, I re-form hospital networks offered by insurers. New networks imply new shares and new premiums in my model, hence I calculate the change in producer surplus. New networks and new premiums imply new utility for consumers, hence I calculate the change in consumer welfare.

Overall, I find that vertical bundling is welfare improving for both consumers and producers. Upon removal of FLF contracts from the market, consumers face wider networks and higher premiums on average. Composition of networks also changes, as insurers shift from covering a block of member hospitals from the same system to covering fewer hospitals per system (but from more systems) and more individual hospitals. Disutility from increased premiums offsets any utility consumers might get from increased choice, therefore consumer welfare drops by $5.9 billion a year. Producer surplus also decreases, however results are mixed for individual hospitals and insurers. Majority of insurers increase their profits as their premiums are higher and their networks contain hospitals from a less restrictive set. The large amount of loss suffered in the hospital industry leads to the decline in overall producer surplus. Some hospital systems lose profits as they can no longer bundle their hospitals together. Some individual hospitals also lose since there are more competitors in the market who are negotiating individually.

These results contribute to several strands of the literature. Hospital-insurer network formation has been an important area of empirical investigation, and a number of papers investigated its determinants and implications.[6] Ho (2009) finds system membership, capacity constraints, and "star" status[7] improve hospitals' leverage in the bargaining process and enable them to achieve higher markups. Ericson and Starc (2015)

[6]For a detailed literature review of firm behavior in the health care industry, see Gaynor et al. (2015).

[7]Star hospitals are defined as providers that are very attractive to consumers.

find consumers have a preference towards larger hospital networks offered by insurers, and this preference gets stronger with age. Ho (2006) investigates welfare impacts of restricted network formation and finds that consumer welfare increases when health plans include all the hospitals in their networks, keeping prices and premiums fixed. While her result is intuitive, it does not allow health plans to change premiums when they widen their networks. I incorporate a bargaining model to her framework, re-form networks based on the bargaining game in my counterfactual, and calculate premiums given new networks by solving insurers' profit maximization problem.

I use the Nash bargaining framework to model hospital-insurer negotiations. This framework was first used in health care research by Brooks et al. (1997) and later extended by several papers.[8] The Nash bargaining game aims to uncover how the total surplus in the market is split between hospitals and insurers based on their bargaining power in the negotiation process. These studies find hospitals -especially ones that belong to systems- have higher bargaining power and extract a higher share of the surplus. Recent papers in this literature (Lewis and Pflum (2015), Gowrisankaran et al. (2015)) assume hospitals negotiate as systems when they model the bargaining game. While this approach is more realistic compared to modeling every hospital as an independent negotiating unit, it is still flawed as not all hospital systems bundle their hospitals together. I improve upon their approach by identifying the hospital systems that engage in bundling and imposing this assumption solely on these systems.

Finally, this paper also contributes to the empirical literature on bundling. While there is a vast literature on the theory of bundling, the empirical literature is sparse, mostly due to lack of data. Crawford and Yurukoglu (2012) analyze bundling practices in cable television industry and simulate a counterfactual where they break bundling and impose an à la carte choice set instead. Their findings indicate that removal of bundling increases utility due to expanded choice sets, but this increase in utility is offset by the increase in prices. They conclude removal of bundling does not have a positive impact on consumer welfare. Their paper is similar to mine in terms of counterfactual simulations and results; however, it analyzes bundling faced by consumers, not by producers. To my knowledge, the only papers that study vertical bundling within supply chain are Ho et al. (2012a, 2012b). These papers model the bundling practices between upstream and downstream firms in the video rental industry in the United States. Ho et al. (2012a) structurally model consumer demand and retailer portfolio choice problem, and use parameter estimates from

[8]For recent papers that study price negotiations in health care, see Gowrisankaran et al. (2015), Lewis and Pflum (2015), Haas-Wilson and Garmon (2011), Dafny et al. (2016), and Ho and Lee (2017).

these models in their counterfactual simulations. Their findings indicate that most of the upstream firms are making the profit maximizing decision when offering full-line forcing contracts. Ho et al. (2012b) analyze the welfare impacts of full-line forcing contracts in the video rental industry by studying their impact on market coverage, leverage, and efficiency. They find that bundling results in increased retailer profits as well as increased product variety and availability for consumers. Hence, they conclude that FLF contracts are welfare improving. My reduced-form analysis adopts the approach used in Ho et al. (2012b), but my structural modeling differs from theirs given the differences in institutional details of the two industries.

The rest of the paper is organized as follows. Section 2 discusses the data. Section 3 presents results from reduced-form regressions. Section 4 outlines the structural model. Section 5 gives estimation details and results. Section 6 explains counterfactual simulations and welfare results. Section 7 concludes.

2 Data

This paper utilizes data from various sources. Hospital characteristics come from American Hospital Association (AHA) Annual Survey of Hospitals 2014. Consumer characteristics and discharge reports come from 2014 State Inpatient Databases (SID) provided by the Health Care Utilization Project (HCUP), and from California Office of Statewide Health Planning and Development (OSHPD) 2014 Public Patient Discharge data.[9] I also use financial data on hospitals reported in OSHPD Financial Disclosure Reports 2008-2014.[10] Insurer characteristics come from Atlantic Information Services (AIS) Directory of Health Plans 2016 with premium and enrollment data being supplemented by the WEISS Ratings Guide. Insurer characteristics from AIS include total enrollment, number of enrolled by sector (commercial risk, public risk etc.) and by state, as well as vertical integration and not-for-profit status. WEISS provides investment ratings of insurers, enrollment, premiums, and number of physicians. Additional plan characteristics are taken from National Committee for Quality Assurance (NCQA) Report on Health Plan Rankings 2015-2016. These characteristics include the type of the insurance plan (HMO, PPO etc.), states served, an overall quality score as well as measures of consumer satisfaction, prevention, and treatment. Hospital networks offered by each insurer are collected from individual insurers' websites in 2017-2018. I also use U.S. Census data on population (by age and sex) and number of uninsured by state to supplement the dataset.

[9]California OSHPD data is used only in bargaining estimation and counterfactual simulations.
[10]Hospital cost function estimation uses this dataset.

Table 1: Patient Characteristics

	Mean	SD	Min	Max
Distance (miles)	15.56	117.25	0.04	428.31
Female	0.66	0.47	0	1
Age	27.68	21.91	0	64

Notes: N=1,152,081 discharges.

I use AIS data on commercial enrollment to identify insurers that operate in each state and collect hospital networks for these insurers. AHA data provides information on where the hospital is located, whether the hospital belongs to a system, and if so, to which system. Given the hand-collected networks and system membership information, I construct FLF measures at hospital and insurer level. A hospital system is considered as an FLF-offering system if all of its hospitals were included in at least one insurer's network in that state. I construct two more measures, one where the system is considered as an FLF-offering system if 80% of its hospitals were included in at least one insurer's network, and the other where 90% of its hospitals were included. I construct these alternative measures because of the discrepancy in the timing of different data sources: AHA data is from 2014, while the hospital networks are from 2017-2018. Due to hospital closures during the course of these four years, the first strict measure of FLF would not accurately identify all FLF-offering systems.[11] Insurer variables are constructed in a similar manner. An insurer is marked as an FLF-accepting insurer if it accepts all hospitals[12] from at least one hospital system in that state. Summary statistics and analyses in the rest of the paper are reported for the alternative measure that uses 80% of system hospitals, the figures for other measures are similar. These alternative measures serve as robustness checks and results of econometric analyses for all three are reported in the appendix.

I use SID data from Arizona, Florida, Kentucky, New Jersey, New York, Rhode Island, and Washington. These states represent over 20% of the entire U.S. population, and cover 1,152,081 discharges from 753 hospitals in total. SID reports patient ZIP code, diagnosis, treatment, age, sex, and charges. I aggregate diagnosis to the 25 Major Diagnostic Categories (MDCs) as defined by the Centers for Medicare Services. I use only in-state, non-emergency-room (non-ER) hospital visits in my analysis. I observe patients' ZIP codes and the hospitals they visited, therefore I calculate the distance between a patient's residence location and hospital location.[13] This data is summarized in Table 1. Average patient in my data travels 16 miles

[11] For example, if a hospital has 16 hospitals in its system in 2014 and 15 hospitals in 2018, the first strict measure of FLF would falsely identify this system as non-FLF even though it is offering FLF contracts. The two alternative measures correct for such mistakes.

[12] Analogously, 80% and 90% of all hospitals for the alternative measures.

[13] Distance is calculated as the distance between two latitude and longitude points of the hospital (as reported by AHA) and the centroid of the patient's ZIP code (as reported by SID).

Table 2: Hospital Characteristics

	All	System	FLF System	Non-FLF System	Individual
Number of Observations	5,960	3,424	2,796	628	2,536
Teaching	0.04	0.05	0.05	0.03	0.04
Beds	77	92	95	72	57
Admissions	5,809	7,168	7,644	5,048	3,975
Physicians	19	20	21	17	17
Nurses per bed	2.62	2.64	2.65	2.61	2.60
Inpatient days	35,144	40,484	40,846	38,837	27,933
For-profit	0.27	0.33	0.30	0.44	0.18
Women's health center	0.49	0.54	0.57	0.41	0.41
Kidney transplant	0.05	0.05	0.05	0.05	0.04
MRI	0.66	0.70	0.74	0.52	0.59
Pain Management	0.52	0.55	0.57	0.45	0.48
System Size	-	8.98	9.21	7.96	1

to get care at a hospital. Females constitute 66% of all discharges due to the large number of pregnancies and childbirths. This paper focuses only on the non-elderly population (ages between 0 and 64) as people above 65 are likely to be enrolled in Medicare plans and I analyze insurers active in the commercial business only. Since all newborns are considered as new patients in this dataset, the average patient is younger than expected.

Table 2 reports means of select characteristics for all hospitals in the United States.[14] I also report the averages of the same characteristics for system hospitals, hospitals that belong to systems that offer FLF contracts, hospitals that belong to systems that do not offer FLF contracts, and individual hospitals.[15] Distribution of individual, non-FLF system, and FLF-offering system hospitals by state are plotted in Figure 1. In Figure 2, I plot the distribution of FLF and non-FLF hospital systems by state.[16]

In 2014, system hospitals constituted 58% of all hospitals in the United States. Among these, 82% belonged to a system that offered FLF contracts. 550 out of 681 hospital systems offer FLF contracts, making 81% of the systems FLF systems. System hospitals are larger on average in terms of general beds compared to individual hospitals. The same pattern is observed when comparing number of admissions and inpatient days. Among the system hospitals, hospitals that belong to FLF-offering systems are larger in terms of

[14]I exclude federal government hospitals (such as Air Force, Navy, Veterans Affairs hospitals) from my analysis as these hospitals do not contract with commercial insurers.

[15]In my dataset, system hospitals are identified as members of systems that operate multiple hospitals in a given state. If a hospital belongs to a national system that operates only one hospital in a certain state, that hospital is coded as an individual hospital in that state for the purposes of my analysis. Hence, the number of systems hospitals should be taken as a lower bound at the national level.

[16]Figure A1 and A2 in the appendix report the same distributions using the strictest definition of FLF.

these measures. Their system size, measured by the number of member hospitals, is also larger on average. System hospitals are better-equipped and offer more services compared to individual hospitals on average, and the same is true when comparing FLF system hospitals to non-FLF system hospitals. According to these figures, hospitals that belong to FLF-systems offer better resources on average, which might make them more appealing to insurers.

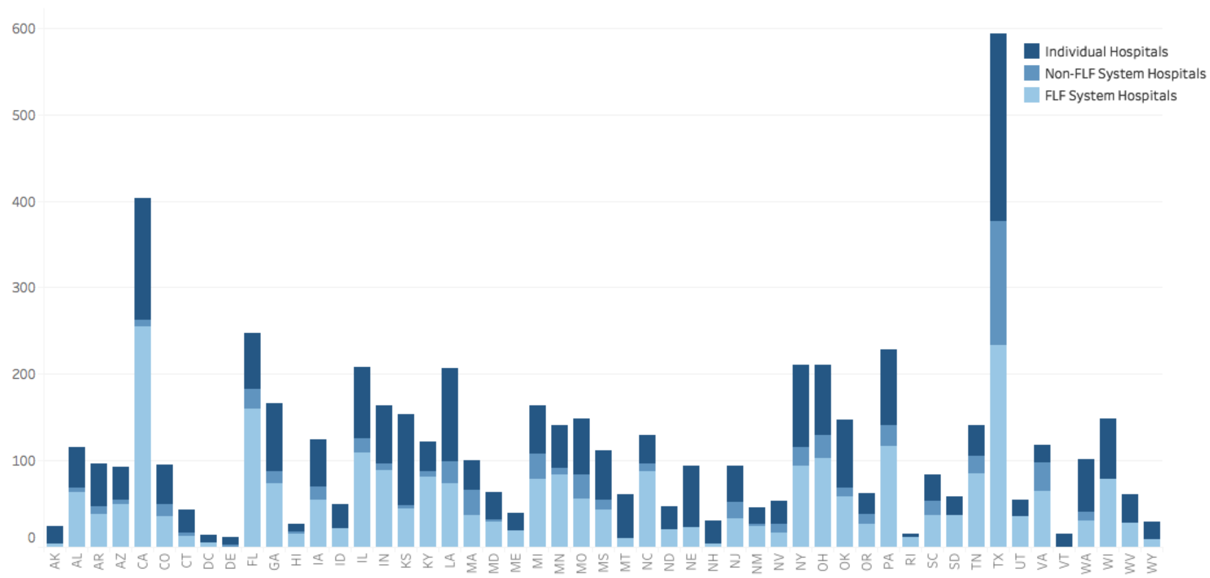

Figure 1: Number of individual, non-FLF system member, and FLF system member hospitals by state

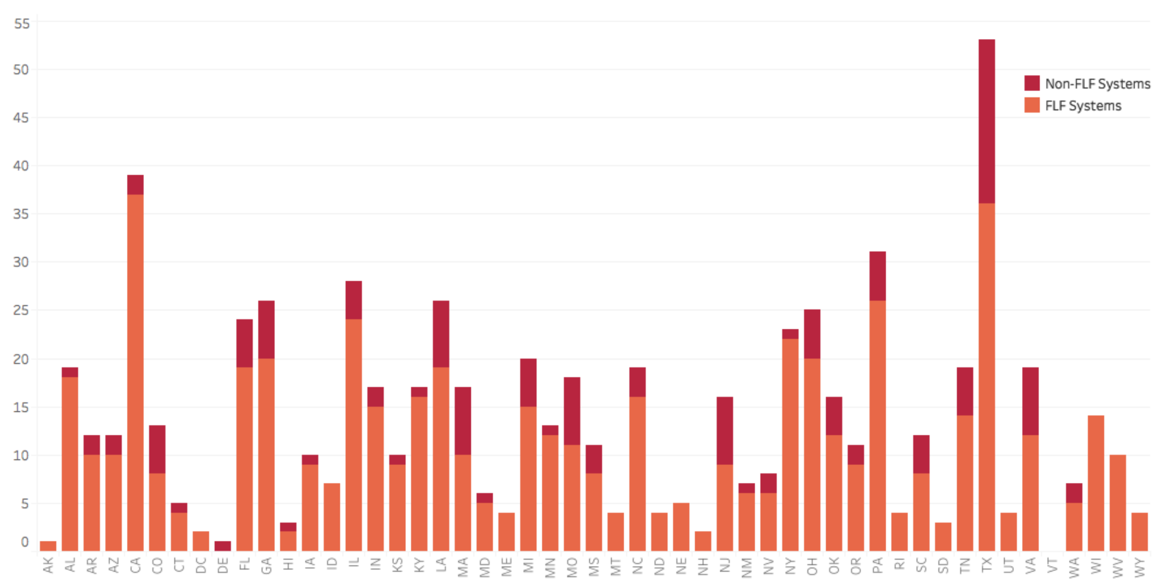

Figure 2: Number of non-FLF and FLF-offering hospital systems by state

Table 3: Health Plan Characteristics

	All	FLF	Non-FLF
Number of Observations	989	827	162
Premiums ($)	348	349	345
Network Size	69	79	15
Pct of Hospitals Covered	0.54	0.59	0.25
Age	46	47	41
Physicians	36,458	37,106	33,149
Total Enrollment	217,255	230,551	149,382
PPO/Indemnity	0.72	0.76	0.5
Consumer satisfaction	3.17	3.18	3.13
Treatment	2.98	2.95	3.16
Prevention	3.17	3.14	3.28
NCQA rating	3.47	3.45	3.60
NCQA accreditation	0.83	0.84	0.75
BCBS	0.45	0.48	0.30

Table 3 reports average health plan characteristics using 989 health plans that operate in 50 states and Washington DC.[17] Average premium per patient per month ranges from $41.7 to $1139.7 with an average of $348.2. The range is large since all types of plans (low-premium HMOs, high-premium indemnity plans etc.) are present in the dataset. The average premium is similar between the insurers that accept FLF and the ones that do not. Average insurer carries 69 hospitals in its network. The average network size of insurers who accept FLF contracts is substantially larger compared to the average network size of the insurers who do not accept such contracts, and this figure is not driven by a possible selection of FLF insurers to larger states. An average insurer in a given state carries 54% of all the hospitals in that state, and this figure is 59% for insurers that accept FLF contracts, but only 25% for insurers who do not. FLF insurers are older on average, include a greater number of physicians in their networks, and have higher enrollment. The average quality ratings differ between the two kinds of insurers based on the measure used. Insurers that accept FLF contracts have higher ratings in terms of consumer satisfaction, however non-FLF insurers have higher ratings in terms of treatment and prevention.[18] Finally, almost half of the insurers that accept FLF contracts are Blue Cross Blue Shield (BCBS) plans that offer large networks and enroll a substantial proportion of the population.

[17] The data reported pertains to 380 distinct insurers. Since many of the national insurers offer plans in multiple states, they are recorded as unique observations as FLF acceptance status and networks change from state to state for these insurers.

[18] The clinical quality measures (treatment and prevention) are calculated using a subset of the Healthcare Effectiveness Data and Information Set (HEDIS) measures whereas consumer satisfaction measure comes from the HEDIS survey which is overseen by AHRQ. Consumer satisfaction measure covers patients' satisfaction with health plans (handling claims, customer service etc.), satisfaction with physicians (doctors' communication, care received etc.), and access of getting care in terms of ease and promptness. The treatment measure evaluates scores in subcategories such as asthma, diabetes, heart attack, and mental health. The prevention score assesses measures such as timeliness of prenatal check ups, breast cancer screening, and early immunizations.

3 Reduced-Form Analysis

3.1 Premiums

In the context of vertical bundling in health care, efficiency gains are expected to realize if hospital systems are able to attain higher profits by offering discounts or lower unit prices for their full-line of products, compared to profits from individually-priced products. If this is the case, insurers that accept FLF contracts will face lower unit costs, and can pass along these savings to their enrollees in the form of lower premiums. To investigate the impact of accepting FLF contracts on insurer premiums, I estimate the following equation using ordinary least squares:

$$lnPremium_j = \beta_0 + \beta_1 FLFinsurer_j + \alpha Z_j + \gamma M_j + D_s + \epsilon_j \tag{1}$$

where the dependent variable is the natural logarithm of insurer j's premium (per enrollee per month), $FLFinsurer_j$ is an indicator variable that takes on a value of 1 if the insurer accepts at least one FLF contract, Z_j are insurer characteristics, M_j are market characteristics, and D_s are state fixed effects.

I estimate equation (1) using national level data where unit of observation is an insurer. The ideal way to investigate the premium-FLF contract relationship would be to use data with insurer-state level observations, as several insurers operate in multiple states and their FLF status change by state. Since my premium data is at the insurer level -I do not observe different premiums charged by the same insurer in different markets-, I am unable to take this approach. Instead, I define $FLFinsurer_j$ to be 1 if insurer j accepts at least one FLF contract in any one of the states it operates in, and investigate its impact on insurers' premiums at the national level. I also aggregate all market-level variables to insurer-level variables using insurer j's enrollments in different states as weights. Finally, I include state fixed effects for every state insurer j operates in.

Results are reported in the first column of Table 4. I do not find any significant effect of accepting FLF contracts on insurer premiums. There are several plausible explanations. First is lack of detailed premiums data at the state level. Second is the potential absence of discounts from upstream entities. Hospital systems may not need to offer discounts to enforce their full-line of hospitals as they have higher bargaining power in the negotiation process (Lewis and Pflum (2015)). Another possible explanation is the failure of insurers to pass along the savings to consumers if they receive the discounts. Finally, differences in compositions of

Table 4: Reduced-form Results

	Premiums	Market Coverage		Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln Premium	Network Size	FLF hospitals	Individual	Non-FLF	Rival FLF
FLF-insurer	0.08	48.18***	25.56***	18.47***	4.15***	1.88***
	(0.09)	(14.46)	(6.84)	(5.35)	(0.91)	(0.10)
Age	-0.003*	0.04	0.03	0.002	0.009	0.003*
	(0.002)	(0.08)	(0.04)	(0.04)	(0.007)	(0.002)
PPO	0.31***	8.10**	3.78**	3.94**	0.37	0.28***
	(0.07)	(3.36)	(1.64)	(1.61)	(0.39)	(0.09)
BCBS	-0.46***	9.52**	4.29*	5.24***	-0.01	0.47***
	(0.10)	(4.00)	(2.50)	(1.50)	(0.37)	(0.09)
Weiss rating	0.03**	2.06**	1.21**	0.79**	0.11	0.07***
	(0.01)	(1.00)	(0.53)	(0.39)	(0.14)	(0.01)
Vertically integrated	-0.23**	-25.43***	-13.88***	-9.41***	-2.15***	-0.94***
	(0.09)	(8.11)	(4.85)	(2.98)	(0.79)	(0.11)
Enrollment	-	0.003	0.001	0.001	0.0006	-0.00002
		(0.003)	(0.002)	(0.001)	(0.0004)	(0.00005)
Observations	380	989	989	989	989	8583
R^2	0.40	0.72	0.74	0.72	0.74	0.53

Notes: Results from ordinary least squares estimation. All specifications include state fixed effects. Enrollment is in thousands. *** statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%.

hospital networks might lead to this result. If FLF-accepting insurers include more system hospitals in their networks compared to insurers that do not accept such contracts, discounts may be offset by higher prices charged by system hospitals (Melnick and Keeler (2007)), making the efficiency effect unobservable to the econometrician.

The rest of the covariates have expected effects on premiums. PPO/indemnity plans offer higher premiums compared HMO/POS plans. Vertically-integrated (VI) insurers offer lower premiums compared to their non-VI counterparts due to elimination of double marginalization. BCBS plans' premiums are lower compared to the rest. This specification also controls for market characteristics such as per capita income, Medicare reimbursement rate to hospitals, hourly mean wage for physicians and surgeons to account for input price, percent black, percent uninsured, unemployment rate, and hospital and insurer market concentration as measured by Herfindahl-Hirschman index. The main finding that accepting FLF contracts does not influence premiums is robust to inclusion of different market characteristics and other covariates. Results are also robust to use of difference measures of FLF, as reported in Table A1 in the appendix.

3.2 Market Coverage

Next, I estimate the following equation to investigate the impact of accepting an FLF contract on insurers' market coverage:

$$NetworkSize_{js} = \beta_0 + \beta_1 FLFinsurer_{js} + \alpha Z_j + D_s + \epsilon_{js} \tag{2}$$

where the dependent variable is the number of hospitals included in insurer j's network in state s, $FLFinsurer_{js}$ indicates whether insurer j accepts at least one FLF contract in state s, and Z_j are insurer characteristics. I also include state fixed effects, D_s, to control for differences in state size. The estimation is done at the insurer-state level as data contains hospital networks offered by insurers at the state level. Standard errors are two-way clustered at the insurer and state level.

Results are reported in the second column of Table 4. Insurers that accept FLF contracts carry 48 more hospitals in their networks, on average, compared to insurers who do not take such contracts. The positive market coverage effect might be arising from the potential discounts given to FLF-accepting insurers. If these insurers face lower unit costs, they might choose to include a greater number of hospitals in their networks. The coefficients in front of the other explanatory variables all have anticipated signs and magnitudes. Insurers with higher enrollment include a greater number of hospitals in their networks. Vertically-integrated health plans carry 25 fewer hospitals on average, whereas BCBS and PPO plans offer larger networks compared to the rest.

In column (3) of Table 4, I report results from a similar estimation where the dependent variable is the number of FLF-offering system hospitals included in insurer j's network in state s. Results indicate that a major portion of the positive market coverage effect can be attributed to inclusion of FLF-offering hospitals. FLF-accepting insurers carry 25 more FLF hospitals in their networks compared no non-FLF insurers. This result is as expected because FLF-accepting insurers carry the full-line of hospitals from FLF systems, whereas non-FLF insurers do not. However, it is important to note that the dependent variable here is all hospitals covered from all FLF-offering systems in the market, regardless of agreement on FLF terms. As such, it includes FLF-offering system hospitals the FLF-accepting insurer successfully contracts on FLF terms as well as other FLF-offering system hospitals whose FLF contracts were not taken. As explained in the next subsection, increased coverage of FLF hospitals by FLF-accepting insurers is due to the increased market coverage in both categories, and does not result solely from the presence of FLF contracts.

3.3 Leverage

The leverage effect is presumed to be present if contracting on FLF terms with at least one system leads to reduced coverage of rival hospitals in the market. In this context, rival hospitals are individual hospitals, non-FLF system hospitals, and FLF system hospitals whose FLF contracts were not taken.

In order to estimate the impact on the inclusion of individual hospitals and non-FLF system hospitals, I estimate the same specification as equation (2), using number of hospitals covered in the relevant category as the dependent variable. Estimating the impact on rival hospitals requires restructuring of the data to insurer-system-state level as rival systems change for each insurer-system pair in a state. To measure the effect of accepting an FLF contract from a system on the number of hospitals covered from other FLF systems whose FLF contracts were not taken by insurer j, I estimate the following equation:

$$Y_{jks} = \beta_0 + \beta_1 FLFother_{js} + \gamma Z_j + D_s + D_k + \epsilon_{jks} \tag{3}$$

where the dependent variable is the number of hospitals covered by insurer j from FLF-offering system k who does not have an FLF contract with insurer j in state s, and the independent variable of interest is whether insurer j has agreed to FLF contracts from any other system. The specification also controls for state and system fixed effects. The sample used here includes only the hospital systems that offer FLF contracts, and excludes insurer-system pairs who successfully contracted on FLF terms.

Results are reported in the last section of Table 4. Insurers that accept FLF contracts carry 18 more individual hospitals and 4 more non-FLF system hospitals, on average, compared to their counterparts. Results from rival FLF system hospital regression exhibit a similar pattern. Accepting an FLF contract from a hospital system does not reduce hospital coverage from rival FLF-offering systems. In fact, FLF-accepting insurers carry 2 more hospitals per system from rival FLF-offering systems, on average, compared to non-FLF insurers. These results are robust to use of alternative FLF measures as well as inclusion of insurer fixed effects, as reported in the appendix.

The absence of leverage effect should be evaluated in relation to the positive market coverage effect. The previous subsection demonstrated that FLF-accepting insurers carry 48 more hospitals in their networks, on average. The decomposition here shows this expansion in market coverage is due to inclusion of not only all member hospitals from FLF-offering systems, but also rival hospitals in all categories. The first plausible explanation is again related to efficiency spillovers. If FLF-accepting insurers receive discounts and hence can include a greater number of hospitals in their networks, they can do so by including rival hospitals. However, it is not likely that these discounts are the only source, especially given the magnitude of the differences in network size. Another possible scenario is that the FLF-offering systems do not offer discounts or offer infinitesimal discounts, yet their FLF contracts are taken due to their high bargaining power. Since system hospital prices are likely to be higher compared to prices of individual hospitals (Melnick and Keeler (2007)), insurers might then choose to include more individual hospitals in their networks to divert their patients to cheaper hospitals.

The overall conclusion from the reduced-form analysis is that FLF contracts should improve consumer welfare. Insurers that accept FLF contracts offer larger networks but not higher premiums. Moreover, these insurers are not including hospitals from FLF systems at the expense of rival hospitals. In order to quantify the change in welfare as well as to understand the network formation strategies of insurers, I structurally model the market in the next section.

4 Structural Analysis: Model and Methodology

The estimation of the structural model consists of three main stages. First, I estimate consumer demand for hospitals and consumer demand for insurance plans. Second, I estimate a cost function to understand how hospital costs are determined. Third, I combine parameter estimates from demand and cost estimation to estimate a bargaining model. The bargaining model captures the hospital-insurer negotiations process and is modeled in a Nash-bargaining framework. Result from all three stages are used in a counterfactual policy experiment where I simulate a market without FLF contracts.

4.1 Estimation of the Demand Side

The vertical relationship between the three agents in the health care market calls for two separate demand models: demand for hospitals by consumers and demand for insurers by consumers. First, I estimate the hospital demand model using a conditional logit framework.[19] Next, I use the results from hospital demand estimation to construct an "expected utility" measure and use this as an insurer characteristic in health plan

[19] I use the standard conditional logit model proposed in McFadden (1974).

demand estimation. This measure captures the predicted utility an average patient gets from a network of hospitals offered by an insurer. Finally, I estimate health plan demand using the contraction mapping algorithm developed by Berry, Levinsohn, and Pakes (1995) (henceforth BLP) taking into account unobserved plan characteristics as well as heterogeneity in consumer preferences towards certain insurer characteristics.

4.1.1 Hospital Demand Model

Let utility of patient i from visiting hospital h in market m given diagnosis l be:

$$u_{ihlm} = u(X_{hm}, V_{ilm}|\lambda, \theta) \tag{4}$$

where (λ, θ) are parameters to be estimated, and X_{hm} is a vector of observed hospital characteristics. $V_{ilm} = [D_{im}, C_{ilm}]$ is a vector of observed consumer characteristics where D_{im} represents demographic characteristics such as sex, age, location and C_{ilm} represents clinical attributes such as diagnosis. Patients choose hospitals to maximize utility, so if patient i with diagnosis l chooses hospital h, then the following inequality must hold for all other hospitals h' in the market, where the market subscript m will be suppressed for notational ease:

$$u_{ihl} = u(X_h, V_{il}|\lambda, \theta) \geq u_{ih'l} = u(X_{h'}, V_{il}|\lambda, \theta) \tag{5}$$

In particular, let the utility specification be:

$$u_{ihl} = \theta X_h + \lambda_1 X_h D_i + \lambda_2 X_h C_{il} - \gamma(V_i) OPC(C_{il}) + \epsilon_{ihl} \tag{6}$$

where $OPC(C_{il})$ is the out-of-pocket cost for patient i with diagnosis C_{il} and γ converts money into utils based on patient characteristics V_{il} and informs us about the price sensitivity of patients.[20] I assume that the independently and identically distributed error term ϵ_{ihl} captures idiosyncratic tastes and has an Extreme Value Type 1 distribution. Then, the hospital share equation can be written as:

$$s_h(\mathcal{M}) = \frac{e^{u(X_h, V_{il}|\lambda, \theta)}}{\sum\limits_{k \in \mathcal{M}} e^{u(X_h, V_{il}|\lambda, \theta)}} \tag{7}$$

where $\mathcal{M}$ is the set of hospitals that are in the same choice set as hospital h. There is no outside option

[20] In practice, a patient's hospital choice depends on out-of-pocket expenditures at a hospital. However, since I do not observe these costs, while estimating the hospital demand model, I make the common assumption (as in Capps et al. (2003), Ho (2006), Lewis and Pflum (2015)) that they are constant across hospitals for a given patient and therefore do not affect hospital choice. Nonetheless, I still estimate the price sensitivity parameter γ jointly with the parameters of the bargaining model.

because I only observe sick patients who are hospitalized. Since I observe the actual shares, I use maximum likelihood to obtain the parameter estimates $\hat{\lambda}$ and $\hat{\theta}$. Identification in this model comes from the variation in patients' hospital choice sets across markets. Unlike the health plan demand model (presented next), this model does not account for unobserved quality of hospitals. I have very rich hospital characteristics data, therefore I assume that the characteristics I use in estimation capture the quality of hospitals.

4.1.2 Expected Utility and Willingness-to-Pay

The hospital demand model presented above is used to create two measures: expected utility from an insurer's network of hospitals (used in insurer demand estimation) and willingness-to-pay (WTP) of an individual for a hospital to be included in his choice set (used in bargaining estimation).[21] The common element to both calculations is patient i's interim utility from having access to a set of hospitals $\mathcal{M}$:

$$V(\mathcal{M}|X_h, V_{il}) = E\Big[\max_{h\in\mathcal{M}} \hat{u}(X_h, V_{il}|\hat{\lambda}, \hat{\theta})\Big] = ln\Big[\sum_{h\in\mathcal{M}} e^{\hat{u}(X_h, V_{il}|\hat{\lambda}, \hat{\theta})}\Big] \tag{8}$$

The expected utility a type q patient[22] gets from a network of hospitals $\mathcal{M}$ offered by insurer j is given by:

$$EU_{qj}(\mathcal{M}) = \sum_l p_{ql}\ V(\mathcal{M}|X_h, V_{ql}) = \sum_l p_{ql}\ ln\Bigg(\sum_{h\in\mathcal{M}} e^{\hat{u}(X_h, V_{ql}|\hat{\lambda}, \hat{\theta})}\Bigg) \tag{9}$$

where p_{ql} is the probability that patient type q is hospitalized with diagnosis l. That is, first I calculate a different interim utility for each diagnosis each patient type q might have. Then, I take a weighted sum across these values where the weights are p_{ql} to calculate the expected utility patient type q receives from having access to insurer j's network of hospitals $\mathcal{M}$. The expected utility measure is calculated for type q patient (instead of individual i) because I do not observe consumers' choices of health plans. Health plan demand estimation uses aggregate shares data to obtain the parameter estimates.

On the contrary, I calculate the WTP measure based on individual i's interim utility because I observe hospital choice at the individual level. The contribution of hospital h to patient i's interim utility from the network of hospitals $\mathcal{M}$ can be calculated as:

$$\Delta_h V(\mathcal{M}|X_h, V_{il}) = V(\mathcal{M}|X_h, V_{il}) - V(\mathcal{M}\setminus h|X_h, V_{il}) = ln\Big(\frac{1}{1 - s_h(\mathcal{M})}\Big) \tag{10}$$

[21] The construction of these measures follows Ho (2006) and Capps et al. (2003), respectively.

[22] Patient types are defined by age-sex-ZIP code cells, where age brackets are 0-17, 18-34, 35-44, 45-54, 55-64.

The total ex-ante WTP for inclusion of hospital h in the network of hospitals $\mathcal{M}$ is then given by integrating (10) across a cumulative distribution of patient characteristics and diagnosis $F(V_{il})$:

$$\Delta W_j(\mathcal{M}) = N_j \int\limits_V \frac{1}{\gamma} ln\Big(\frac{1}{1 - s_h(\mathcal{M})}\Big) dF(V_{il}) \tag{11}$$

where N_j is the number of patients enrolled with insurer j that visit a hospital.

4.1.3 Insurer Demand

I estimate consumer demand for insurers using a discrete choice setting that accounts for unobserved individual characteristics as well as the expected utility a patient gets from a network of hospitals. I start by estimating a benchmark logit model that closely follows the specification in Berry (1994) and then move onto BLP estimation that takes into account heterogeneity in individual preferences towards insurer characteristics as an additional layer.

Logit Model:

Let utility individual i gets from plan j in market r be:

$$w_{ijr} = \sum_k x_{jkr}\beta_k + \xi_{jr} + \epsilon_{ijr} \tag{12}$$

where x_{jkr} is the k^{th} observed plan characteristic of plan j and ξ_j represents the unobserved plan characteristic (such as patients' perception about quality, status, service, reputation, past experience etc.). For simplicity, I drop the market subscripts in the rest of the analysis. Therefore, the utility function can be written as:

$$w_{ij} = \sum_k x_{jk}\beta_k + \xi_j + \epsilon_{ij} = \delta_j(x_j, \xi_j, \beta) + \epsilon_{ij} \tag{13}$$

where δ_j represents the mean utility level from plan j. The unobserved characteristics are assumed to be mean independent of x_j's and also independent across markets. The error term ϵ_{ij} is independently and identically distributed across consumers and plans and assumed to have an Extreme Value Type 1 distribution. Normalizing the mean utility from the outside good to be zero (i.e. $\delta_o = 0$), the closed-form solution for the market share equation for product j can be written as:

$$s_j = \frac{e^{\delta_j}}{1 + \sum_{g=1}^{G} e^{\delta_g}} \tag{14}$$

where G is the number of plans in the market. The share of the outside good is given by:

$$s_o = \frac{1}{1 + \sum_{g=1}^{G} e^{\delta_g}} \tag{15}$$

Dividing equation (14) by equation (15) gives:

$$\frac{s_j}{s_o} = e^{\delta_j} \Longrightarrow ln(s_j) - ln(s_o) = \delta_j \tag{16}$$

Hence, I generate δ's using the market share data. Having obtained the dependent variable, I estimate the following equation to obtain the parameter estimates:

$$\delta_j = \sum_k x_{jk}\beta_k + \xi_j \tag{17}$$

Before moving on with estimation, the endogeneity problem caused by premiums needs to be addressed. The unobserved plan characteristic ξ_j (the error term in equation (17)) is likely to be correlated with the plan's premium which is one of the observed plan characteristics. One would expect a high-quality, better-service plan to charge a higher premium. For this reason, I instrument for the premium variable. Traditional instruments used in the literature for price are cost shifters (these are difficult to find as they are usually correlated with ξ's), characteristics of competing products in the same market, and prices of the same product in other markets (because a shock to marginal cost will be carried to prices in other markets). I use characteristics (other than premium) of other plans within the same market as instruments. These instruments and the relevant validity tests are further discussed in section 5. Given these instruments Z, I form the moment conditions as follows. First, I calculate the unobserved quality term ξ_j as a function of model parameters:

$$\xi_j = \delta_j - \sum_k x_{jk}\beta_k = ln(s_j) - ln(s_o) - \sum_k x_{jk}\beta_k \tag{18}$$

The instruments should be orthogonal to this unobserved quality term, so I form the moment conditions as $E[\xi(\beta)'Z] = 0$. In applying iterative Generalized Method of Moments (GMM), I use the "optimal" weighting matrix W which is the inverse of the variance of moment conditions. Therefore, the problem reduces to:

$$\min_{\beta} \xi(\beta)' Z W Z' \xi(\beta) \quad where \quad W = (E[Z'\xi\xi' Z])^{-1} \tag{19}$$

The analytical solution to this problem is:

$$\beta = (X'ZWZ'X)^{-1}(X'ZWZ'\delta) \tag{20}$$

The iterative estimation algorithm starts with $W = (Z'Z)^{-1}$ to get an initial estimate $\hat{\beta}$, and then I re-compute $W = (E[Z'\xi(\hat{\beta})\xi(\hat{\beta})'Z])^{-1}$ to get a new estimate of β.

Identification in the health plan demand model comes from the variation in consumers' choice sets across markets as well as the variation of health plan characteristics within a market. Markets are defined by states. Results from the health plan demand estimation are presented in Table 6.

BLP:

The major drawback of the previous model is that it does not generate realistic substitution patterns. In this setting, the cross-price elasticity between any two plans depends only on their market shares. Consider two health plans A and B whose market shares are the same. Let A be an HMO plan with low premiums, narrow hospital and physician networks, and low ratings; and B be a PPO plan with high premiums, large provider network, and top ratings. Assume there is another PPO plan C in the market with high premiums, large provider network, and high quality ratings. The cross-price elasticity of the previous model implies that if plan C increases its premiums, the demand for plan A and plan B will increase equally. This is unintuitive as we expect the cross-price effect to be larger for health plans that are similar in characteristics. The model presented by BLP solves this problem and generates realistic substitution patterns. With the BLP estimation outlined below, cross-price elasticities are larger for products that are closer together in terms of their characteristics.

Let utility of patient i from insurer j in market r be:

$$w_{ijr} = \xi_{jr} + x_{jr}\phi + \beta_1 EU_{jr} + \beta_2 Prem_{jr} + \gamma_1\nu_{i1}EU_{jr} + \gamma_2\nu_{i2}Prem_{jr} + \eta_{ijr} = \delta_j + \mu(\nu_{i1}, \nu_{i2}) + \eta_{ijr} \tag{21}$$

where ξ_j are unobserved insurer characteristics, x_j are observed insurer characteristics, $Prem_j$ is insurer j's premium, ν_i are random draws from a normal distribution and represent unobserved individual preferences, and η_{ij} are idiosyncratic shocks to consumer tastes that are assumed to be independently and identically distributed with Extreme Value Type 1. The expected utility measure presented in the previous subsection is aggregated to insurer level by taking a weighted sum across patient types where weights are population shares of type q individuals obtained from Census data. δ_j is the mean utility level that a patient gets from plan j. It is the presence of the interaction terms μ that allows me to capture the heterogeneity of preferences. In this setting, consumers with similar characteristics prefer similar products. Therefore, if an insurer is removed from the choice set, consumers will substitute to other insurers that are similar in terms of characteristics and this generates more realistic substitution patterns.

Identification in this model comes from the variation in patients' plan choice sets across markets. To address the endogeneity issue, I again instrument for premiums using the BLP-type instruments mentioned above. The outside good is defined as having no insurance and its share is calculated using the Census data. In this setting, the share equation for plan j cannot be solved analytically. As in BLP, I use simulation techniques to obtain the predicted shares:

$$\hat{s_{jr}}(\phi,\gamma,\beta) = \frac{1}{ns}\sum_{i=1}^{ns}\frac{e^{(\xi_{jr}+x_{jm}\phi+\beta_1 EU_{jr}+\beta_2 Prem_{jr}+\gamma_1\nu_{i1}EU_{jr}+\gamma_2\nu_{i2}Prem_{jr})}}{1+\sum_{k\in P}e^{(\xi_{kr}+x_{kr}\phi+\beta_1 EU_{kr}+\beta_2 Prem_{kr}+\gamma_1\nu_{i1}EU_{kr}+\gamma_2\nu_{i2}Prem_{kr})}} \tag{22}$$

where ns is the number of random draws (1000 in my estimation), and P is the set of plans in the market. That is, I calculate a different share with each distinct draw of the unobserved individual preference term ν_i, and then obtain the predicted share as an average of these simulated shares across draws. Dropping the market subscript and simplifying notation, one can write the predicted shares as:

$$\hat{s_j}^{ns} = \frac{1}{ns}\sum_i \frac{e^{\delta_j+\mu(x_j,\nu_i)}}{1+\sum_j e^{\delta_j+\mu(x_j,\nu_i)}} \tag{23}$$

Given the equation for predicted shares, I use the contraction mapping algorithm introduced by BLP to obtain δ, the mean utility level vector. This algorithm aims to match the predicted shares $\hat{s}$ to the observed true shares s using the following equation:

$$\delta^h = \delta^{h-1} + ln(s) - ln(\hat{s}) \tag{24}$$

I begin by evaluating the right-hand side at an initial guess of parameters and δ, obtain a new δ, put it back into the right-hand side and repeat this until convergence is reached. Once I obtain δ, I rewrite the unobserved plan characteristics as $\xi_j = \delta_j - x_j\phi$. Therefore, I form the moment conditions as $E[\xi' Z] = 0$ and estimate via GMM.

4.2 Hospital Cost Function

I adapt the trans-log specification common in the literature (Fournier and Mitchell (1997), Capps et al. (2010), Lewis and Pflum (2015)) that is used to estimate cost functions of multiproduct firms and hospitals. According to this specification, hospital h's costs at time t are given by:

$$\begin{aligned} ln(Cost_{ht}) = \beta_0 \ + \ \beta_1 ln(Y_{ht}) \ + \ \beta_2 ln(Y_{ht}) \times ln(Y_{ht}) \ + \ \beta_3 ln(W_{ht}) \ + \ \beta_4 ln(W_{ht}) \times ln(W_{ht}) \\ + \ \beta_5 ln(Y_{ht}) \times ln(W_{ht}) \ + \ \kappa_{ht} \ + \ t \ + \ \epsilon_{ht} \end{aligned} \tag{25}$$

where Y_h are hospital outputs, W_h are hospital inputs, κ are hospital fixed effects, and t is a time trend. The error term ϵ_{ht} is clustered at the hospital level, therefore it is allowed to be correlated for a hospital across years, but errors are assumed to be distributed independently across hospitals. The dependent variable is the natural logarithm of the total operating costs at a hospital. The hospital output vector, Y_h, consists of inpatient days and outpatient visits for private insurance, Medicare, and other payer types (such as Medi-Cal, workers' compensation, county indigent programs, self-pay etc.). The hospital input vector, W_h, includes size measures for the hospital (such as number of beds, fixed assets, total number of hours for registered nurses etc.), governance structure, for-profit status, rural status, vertical integration status, teaching status, and FLF status. The marginal costs of both components are allowed to vary by other inputs and outputs through the inclusion of the interaction terms. The results from hospital cost function estimation are presented in Table A3 in the appendix.

4.3 Bargaining

The model used for bargaining estimation closely follows the specification in Lewis and Pflum (2015).[23] I use the Nash bargaining framework where the two agents negotiate to split the surplus they jointly generate by successfully contracting. The outcome of the bargaining game is a contract equilibrium as in Crémer and

[23]Different from their setup, I estimate the model at the insurer-hospital and insurer-system level using data on insurer enrollment instead of aggregating the estimating equation to the hospital level. I explain data and variable construction for each specification in detail in the next section.

Riordan (1987) that relies on the following assumptions:

1. All hospital-insurer pairs negotiate contracts simultaneously.

2. All hospital-insurer pairs negotiate under the anticipation that all other hospital-insurer pairs will successfully negotiate contracts.

3. The bargaining outcome between a hospital and an insurer does not influence the bargaining outcome of these parties with other insurers and hospitals.

4. When a hospital is removed from a choice set, patients re-allocate themselves to other hospitals in the same choice set.

Given these assumptions, the objective function of the Nash bargaining game is:

$$\max_{p_{hj}}[\Pi_h(\mathcal{H}) - \Pi_h(\mathcal{H}\backslash j)]^{\alpha_h}[\Pi_j(\mathcal{M}) - \Pi_j(\mathcal{M}\backslash h)]^{1-\alpha_h} \tag{26}$$

where $\Pi_h(\mathcal{H})$ are profits of hospital h when it contracts with a set of insurers $\mathcal{H}$, $\Pi_h(\mathcal{H}\backslash j)$ are profits of hospital h when it contracts with the same set of insurers except insurer j, $\Pi_j(\mathcal{M})$ are profits of insurer j when it contracts with a set of hospitals $\mathcal{M}$, $\Pi_j(\mathcal{M}\backslash h)$ are profits of insurer j when it contracts with the same set of hospitals except hospital h, p_{hj} are the negotiated prices between hospital h and insurer j, α_h represents the bargaining power of hospital h, while $1-\alpha_h$ represents the bargaining power of insurer j.

The objective function can be expressed as $\max_{p_{hj}}[\Delta_j\Pi_h]^{\alpha_h}[\Delta_h\Pi_j]^{1-\alpha_h}$ where:

$$\Delta_j\Pi_h = \Pi_h(\mathcal{H}) - \Pi_h(\mathcal{H}\backslash j) = p_{hj}D_h(\mathcal{M}) - \Delta C_h(D_h(\mathcal{M})) \tag{27}$$

$$\Delta_h\Pi_j = \Pi_j(\mathcal{M}) - \Pi_j(\mathcal{M}\backslash h) = \Delta W_j(\mathcal{M}) - \Delta R(p_{\mathcal{M}j}) \tag{28}$$

In the above expressions, the change in hospital h's profits, $\Delta_j\Pi_h$, is the difference between the additional revenues it will generate $(p_{hj}D_h(\mathcal{M}))$ and the additional costs it will bear $(\Delta C_h(D_h(\mathcal{M})))$ by contracting with insurer j, as a result of the expected change in hospital visits that emerges from insurer j's enrollees $(D_h(\mathcal{M}))$. The change in insurer j's profits by successfully negotiating a contract with hospital h, $\Delta_h\Pi_j$, is the difference between the change in WTP of its enrollees $(\Delta W_j(\mathcal{M}))$ to have access to hospital h and the change in insurer j's total reimbursements $(\Delta R(p_{\mathcal{M}j}))$ when hospital h is included in its network, compared to the reimbursements when hospital h is not available as an option and the enrollees visit other hospitals instead. Formally, $\Delta R(p_{\mathcal{M}j}) = \sum_{k \in \mathcal{M}} p_{kj} D_k(\mathcal{M}) - \sum_{k \in \mathcal{M} \setminus h} p_{kj} D_k(\mathcal{M} \setminus h)$.

Inserting these expressions into the objective function and taking the first order condition leads to the estimating equation:

$$\Delta_j \Pi_h = \alpha_h [\Delta W_j(\mathcal{M}) - \Delta C_h(D_h(\mathcal{M})) - \Delta R_j(p_{\mathcal{M}j}) + p_{hj} D_h(\mathcal{M})] \tag{29}$$

All the elements of equation (30) can be calculated from the previous parts of the structural model. Change in WTP, $\Delta W_j(\mathcal{M})$, is calculated as in equation (11), using results from hospital demand estimation. Change in costs, $\Delta C_h(D_h(\mathcal{M}))$, is calculated by predicting the change in hospital days using the hospital demand function, and then using these in hospital cost function to obtain predicted change in costs. Change in reimbursements of insurer j, $\Delta R_j(p_{\mathcal{M}j})$, are calculated by using the hospital demand model to predict how patients will re-allocate themselves to other hospitals if insurer j fails to successfully contract with hospital h. Finally, change in hospital revenues, $p_{hj} D_h(\mathcal{M})$, are calculated by using the predicted change in hospital visits if a contract is reached, again using the estimates from the hospital demand model. The only unknown, and the parameter of interest, is therefore the bargaining power α_h. I further parameterize α_h as follows in order to analyze how hospital bargaining power is determined:

$$\alpha_h = \alpha_0 + \beta H_h + \eta M_h + \epsilon_h \tag{30}$$

where H_h are hospital characteristics such as FLF status, teaching status etc., and M_h are market characteristics such as HHI measure of market concentration. Therefore, I take the following equation to estimation and use nonlinear least squares[24] to obtain the parameter estimates:

$$\Delta_j \Pi_h = (\alpha_0 + \beta H_h + \eta M_h)[\Delta W_j(\mathcal{M}) - \Delta C_h(D_h(\mathcal{M})) - \Delta R_j(p_{\mathcal{M}j}) + p_{hj} D_h(\mathcal{M})] \tag{31}$$

In the above equation, the term in brackets is the surplus generated by hospital h and insurer j successfully signing a contract. Identification in this model comes from the variation that identifies each individual component of surplus. In particular, parameters of the hospital demand model are identified by the variation in patients' choice sets across markets, while the parameters of the hospital cost function are identified by relating the variation in hospital costs to the variation in observable hospital input and output data. The

[24] Consumer price sensitivity parameter γ is estimated via this equation and is a part of the WTP measure $\Delta W_j(\mathcal{M})$ as defined by Equation (11).

parameters of the bargaining model are identified by relating the variation in change in hospital profits to predicted surplus that varies by the above-mentioned sources. Therefore, the parameters are mainly identified by variation in the data as opposed to the functional form.

5 Structural Analysis: Estimation Details and Results

5.1 Hospital Demand Estimation

The hospital choice model uses two data sources: patient characteristics come from SID for Arizona, Florida, Kentucky, New Jersey, New York, Rhode Island, and Washington while hospital characteristics come from AHA Survey. I estimate a conditional logit model where the utility specification[25] is given by:

$$u_{ihl} = \theta X_h + \lambda_1 X_h D_i + \lambda_2 X_h C_{il} + \epsilon_{ihl} \tag{32}$$

where X_h is a vector of observed hospital characteristics, D_i is a vector of demographic characteristics such as sex, age, location, and C_{ilm} is a vector of diagnosis. One of the interaction terms $X_h D_i$ is the distance the patient travels to visit a hospital. In the model presented here, patients' choice sets are defined by ZIP codes. In particular, I put a hospital in a patient's choice set if another patient who lives in the same ZIP code visited that hospital.[26]

Table 5 presents a subset[27] of results from hospital demand estimation. Most hospital characteristics and services offered have positive coefficients that are highly significant. Same is true for the interaction terms. Consistent with the previous findings in the literature, I find that having to travel an extra mile to get treated at a hospital decreases the odds of that hospital being chosen by 3%.[28] Odds of an FLF hospital being chosen is 1.04 times higher compared to an individual or non-FLF system hospital. Similarly, odds of being chosen is 1.05 times higher for a VI hospital compared to a non-VI one if both hospitals are at zero distance to the patient. Finally, patients are more likely to visit hospitals that offer services that are

[25] While the original specification includes out-of-pocket costs (OPC), I exclude this term here as I do not observe it. The coefficient in front of OPC is estimated along with the bargaining parameters, see Table 7.

[26] I also estimated specifications where I constructed choice sets based on the Hospital Service Area (HSA) and Hospital Referral Region (HRR) of the hospital the patient visited and obtained similar results. In an ideal world, I would construct the choice sets based on the hospital network the patient's insurer offers. Unfortunately, I do not observe which individual is enrolled in which health plan in any of my datasets, therefore I cannot take this approach.

[27] For the full set of coefficient (not odds ratio) estimates, see Table A2.

[28] The figure reported is for a male patient aged between 55-64 who visits a non-VI hospital. The effect of distance decreases (becomes more negative) in various individual characteristics such as female and age.

Table 5: Hospital Demand Estimation

Variable	Odds Ratio	Variable	Odds Ratio
Distance (miles)	0.97*** (0.0001)	Ultrasound	1.42*** (0.02)
VI hospital	1.05*** (0.005)	Orthopedic services	1.02** (0.01)
FLF hospital	1.04*** (0.003)	Birthing room x Female	1.16*** (0.02)
Distance x Female	0.987*** (0.0001)	Adult cardiac surgery x Circulatory system	3.67*** (0.09)
Distance x Age (18-34)	0.98*** (0.0002)	Burn care x Burns	42.35*** (5.43)
Nurses per bed	1.24*** (0.003)	Neurological services x Nervous system	2.50*** (0.08)
Teaching hospital	1.06*** (0.005)	Hemodialysis x Kidney and urinary tract	1.41*** (0.04)
Medical/surgical care	1.29*** (0.02)	Oncology services x Blood disorders	2.14*** (0.24)
Chemotherapy	1.18*** (0.008)	Obstetrics care x Pregnancy and childbirth	97.10*** (4.66)
Fertility clinic	1.02*** (0.006)	Fertility clinic x Female	0.96*** (0.006)

Notes: Results from maximum likelihood estimation. N=1,152,081 hospital discharges from 7 states. See Table A2 for a full set of covariates included in the estimation. Standard errors in parentheses. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

related to their diagnosis. For example, the effect of an adult cardiac surgery unit for a patient diagnosed with a circulatory system disease is 3.7 times that of a patient who is not diagnosed with circulatory system disease, as anticipated.

5.2 Insurer Demand Estimation

The insurer demand model uses data at the national level. A market is defined as a state since health plans are observed to serve residents of specific states. An insurance plan is assumed to be a competitor in a market if it serves the residents of that state. The logit framework I use takes into account unobservable plan characteristics and is estimated via GMM. The utility function is of the form:

$$w_{ij} = \sum_k x_{jk}\beta_k + \xi_j + \epsilon_{ij} = \delta_j(x_j, \xi_j, \beta) + \epsilon_{ij} \tag{33}$$

where the observable insurer characteristics x_j are FLF-accepting insurer indicator, VI insurer indicator, insurer premium per person per month (in \$100s), expected utility, age of the insurer, physicians per 100 population, Weiss rating, NCQA rating, NCQA accreditation, prevention quality measure, PPO indicator, BCBS indicator, and a large plan indicator.[29] In addition to these variables, the BLP specification includes interactions of expected utility and premiums with random draws to capture heterogeneity in individual preferences. Both specifications also include state fixed effects.

Since premiums are endogenous, I instrument for them using the average of characteristics of other plans $(x_n, n \neq j)$ in the same market. These characteristics are Weiss rating, prevention, age, number of physicians, expected utility, and NCQA rating. These instruments satisfy the three traditional conditions of instrumental variables. They are relevant as they are correlated with premiums via competition and markups[30], they are uncorrelated with the error term, and they affect utility only through their impact on premiums. To further support the choice of the instruments, I analyze two statistics. The first stage results report a partial R-squared of 0.72 and an F-statistic of 17.46. These statistics suggest a large portion of the unexplained variation in premiums comes from the excluded instruments and the instruments are not weak since the F-statistic is greater than 10.[31]

[29] I define an insurer as large if it operates in multiple states. According to this definition, I mark Aetna, Anthem, BCBS, CIGNA, Humana, Kaiser Permanente, United Healthcare as large health insurers. Consumers perceptions about these plans are likely to be reflected in their preferences.

[30] This relationship is implied by the first order conditions in the supply side that leads to the pricing Equation (37).

[31] See Bound et al. (1995).

Table 6: Insurer Demand Estimation

	(1)	(2)
Premium ($00)	-0.63*	-0.22***
	(0.37)	(0.05)
NCQA rating	0.72	-0.33
	(0.55)	(0.36)
NCQA accreditation	0.63	0.46
	(0.42)	(0.39)
VI-insurer	0.96**	0.19
	(0.48)	(0.44)
FLF-insurer	0.22	0.76
	(0.33)	(0.78)
Age	-0.001	0.007*
	(0.005)	(0.004)
Weiss rating	-0.10***	-0.11***
	(0.03)	(0.04)
Physicians	0.008***	0.001***
	(0.0003)	(0.0002)
Prevention	-0.94**	-0.15
	(0.44)	(0.30)
Expected utility	0.46***	0.49***
	(0.03)	(0.03)
PPO	1.10*	-0.001
	(0.66)	(0.26)
Large Insurer FE	Yes	Yes
BCBS FE	Yes	Yes
State FE	Yes	Yes

Notes: Results from GMM estimation. N=989 insurers from 50 states and Washington DC. Robust, clustered (at the state level) standard errors in parentheses. First column follows Berry (1994), second column follows BLP (1995). Physicians are per 100 enrollee population. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

To complete the estimation, the last element needed is the share of the outside good. Since I observe HMO/POS and PPO/indemnity plans in my data, I define the outside good as being uninsured. U.S. Census reports number of uninsured and state population by age group. Therefore, I calculate the share of the outside good, s_0, by dividing the number of nonelderly uninsured by nonelderly population of that state.

The parameter estimates are reported in Table 6. The first column reports results from Berry (1994) specification while the second column presents results from the BLP estimation. The coefficient in front of premiums is negative and significant as expected. Its magnitude implies an average insurer-perspective elasticity of -2.11.[32] This suggests that a \$10 increase in monthly premiums per enrollee decreases the demand for that insurer by 6%. The expected utility coefficient is positive and significant, implying people value the hospital network offered by an insurer while making their choices. The parameter estimate for FLF insurer indicator is positive, however not statistically significantly different than zero. This is reasonable as inclusion of FLF hospitals in insurer networks as well as characteristics of these hospitals are captured in the expected utility term. As logit and BLP specifications give similar coefficients in terms of sign, magnitude, and significance; I use the estimates from the BLP model in counterfactual estimations as this model better captures individual heterogeneity in preferences and creates more realistic substitution patterns.

5.3 Bargaining

The estimating equation for the bargaining model is:

$$\Delta_j \Pi_h = (\alpha_0 + \beta H_h + \eta M_h)[\Delta W_j(\mathcal{M}) - \Delta C_h(D_h(\mathcal{M})) - \Delta R_j(p_{\mathcal{M}j}) + p_{hj} D_h(\mathcal{M})] = \alpha_h \times \Delta S_{hj}(\mathcal{M}) \quad (34)$$

where $\Delta \Pi_h$ are the additional profits earned by hospital h when it successfully signs a contract with insurer j, the first term in parentheses is the decomposition of hospital bargaining power, while the second term in brackets is the total surplus generated by insurer j and hospital h successfully negotiating a contract. In this model, hospital h's bargaining power is determined by market characteristics M_h such as hospital market HHI, as well as its own characteristics H_h such as FLF status, VI status, teaching status, rural status, market share, integration with a physician group, system membership etc. The elements of total surplus are each calculated using the models in the previous steps, and their calculations are detailed below. In an ideal world, the bargaining model would be estimated using data on negotiated prices between each

[32] This is the elasticity of demand with respect to premiums from insurer's perspective, as opposed to the elasticity from the consumer's perspective that is based on out-of-pocket expenditures.

hospital-insurer pair, the insurance plan the individual is enrolled in, and the hospital he/she visited. While I observe the hospital visited by each patient in my data, I do not observe what health plan he/she is enrolled in. Lewis and Pflum (2015) encounter the same problem, and aggregate the bargaining equation to the hospital level, and estimate the following equation at the hospital level:

$$\sum_{j \in \mathcal{H}} \Delta_j \Pi_h = \alpha_h \times \sum_{j \in \mathcal{H}} \Delta S_{hj}(\mathcal{M}) \tag{35}$$

where every term is summed across the set of insurers the hospital contracts with, $\mathcal{H}$. They also use assumed shares from insurers at a hospital when calculating individual elements of surplus. I extend their setup by using data on insurers and estimating the bargaining model at the hospital-insurer level. Since I observe insurer networks as well as market shares, I disaggregate the hospital level components of surplus into hospital-insurer level by using the share of insurer for each hospital. For example, in the model outlined above, $\Delta W_j(\mathcal{M})$ is the total WTP of the enrollees for hospital h to be included in insurer j's network. Following equation (35), I first calculate the total WTP of *all* patients in the market for hospital h. Then, I split this WTP measure into WTP for hospital h of each insurer, based on market shares.[33] Therefore, if the share of patients at hospital h from insurer j is $s_{jh}^{ins-hosp}$, then the WTP of enrollees of j for hospital h is $\Delta W_h \times s_{jh}^{ins-hosp}$ where ΔW_h is the total WTP for hospital h.

In what follows, I discuss the calculation of each element of surplus and then discuss results from the bargaining model. I use data from California OSHPD to estimate the bargaining model and obtain welfare results. One thing to note is that hospital demand model forms the basis of components in bargaining model, therefore I start by estimating hospital demand. Different from the hospital demand model discussed above, I use choice sets based on Hospital Referral Regions (HRRs)[34] and omit the individual-level variables.[35] I estimate this demand model with the same set of SID states, and then use the parameter estimates to predict what hospital shares would be in California. I cannot adopt the alternative approach to create choice sets based on ZIP codes as patient ZIP codes are not reported in California data.[36]

[33] Calculation of the share of patients at a hospital from an insurer is outlined in the appendix.

[34] I also tried using the estimates from choice sets based on the narrower geographic measure, Hospital Service Areas (HSAs). Since many of the HSAs have only 1 hospital, these choice sets needed to be dropped while calculating change in insurer reimbursements when an agreement is not reached, as this calculation requires patients to re-allocate themselves to other hospitals in their choice sets. Moreover, having a single hospital in a choice set is not credible as many patients choose from multiple hospitals as opposed to one. Therefore, I conducted my analysis using HRR choice sets.

[35] Bargaining model uses data from California OSHPD. While previous papers in the literature used individual-level variables from the same data source, OSHPD stopped reporting these variables to protect patient confidentiality starting with 2012 data. Therefore, I am unable to use terms involving sex and age in hospital demand estimation and prediction, as these are unavailable in the California data.

[36] Starting with 2012 data, OSHPD only reports the first 3 digits of a patient's ZIP code. Based on this, I randomly assign

For each component of total surplus, I follow calculations in Lewis and Pflum (2015) to obtain hospital level aggregate measures. The basis of the first element, ΔW_h, is the total WTP for hospital h. I calculate the WTP of each individual for each hospital as $ln(1/(1-\hat{s_{ih}}))$ where $\hat{s_{ih}}$ is the predicted probability that patient i will choose hospital h. Then, I sum this across individuals for every hospital to obtain ΔW_h. Then, the WTP of enrollees of insurer j for hospital h to be included in j's network is calculated as $\Delta W_j(\mathcal{M}) = \frac{1}{\gamma} \times \Delta W_h \times s_{jh}^{ins-hosp}$ following Equation (11).

The second element of surplus, $\Delta C_h(D_h(\mathcal{M}))$, is the expected change in hospital costs when hospital h joins insurer j's network. This term is calculated using both hospital demand model and hospital cost function. First, I estimate the hospital cost function where hospital costs depend on hospital inputs and outputs such as inpatient days from private payers, inpatient days from Medicare etc. Next, using results from hospital demand, I predict private[37] inpatient days at a hospital ($predDays$) by multiplying predicted probability of choice with length of stay, and summing it across private patients for a particular hospital. Finally, using parameter estimates from hospital cost function, I predict hospital costs using two output measures: $predDays$ and $(1 - s_{jh}^{ins-hosp}) \times predDays$. The difference between the two predicted costs gives the change in costs at a hospital if it contracts with insurer j.

The third component of surplus, $\Delta R_j(p_{\mathcal{M}j})$, is the change in reimbursements of an insurer if it does not include hospital h in its network and its patients re-allocate themselves to the remaining hospitals.[38] The outline of the calculation is as follows. For every hospital h, I remove h from the market, focus on the choice set affected by removal of h, re-assign h's patients to other hospitals in this choice set based on the demand model, and then calculate extra revenues at these hospitals. Finally, I get an extra revenue per hospital which is equivalent to extra reimbursement the hospital gets from all the insurers it contracts with. I then decompose this to hospital-insurer level based on shares $s_{jh}^{ins-hosp}$. The detailed calculation of these steps

individuals to ZIP codes starting with those 3 digits based on ZIP codes' population weights, and use this to calculate distance to be used in prediction. However, as these ZIP code assignments are not precise, I refrain from using them as choice sets in hospital demand estimation. Estimating hospital demand using exact distances from SID gives me more accurate coefficients for the covariates, and especially for distance.

[37] As I only work with commercial insurers in my data, I only consider changes in the private line of business.

[38] In an ideal world, I would calculate this component using insurer networks as choice sets. However, I do not observe which individual is enrolled in which health plan, so I am forced to use HRRs as my choice sets. While the re-assignment of patients to other hospitals in patient choice sets would be more precise with insurer networks as choice sets, since the final product is calculated at the hospital level and then decomposed to hospital-insurer level based on $s_{jh}^{ins-hosp}$, I assume the hospital level aggregated measure is close when using HRR choice sets to what it would be if I used insurer networks as choice sets. The choice sets in Lewis and Pflum (2015) are also not based on insurer networks (except top five largest HMOs), and they conduct a similar analysis to obtain the change in reimbursements of insurers using ZIP code choice sets. Finally, I drop choice sets with only 1 hospital as patients are unable to re-allocate themselves if they belong in these choice sets.

is as follows. First, for every hospital that is removed from the market, I calculate predicted extra days at other hospitals that are in the same choice set. If hospital h is removed from the choice set, then the predicted extra days at hospital h' are calculated as: $extraPredDays_{h'} = \left[\frac{prob_{h'}}{1-prob_h} - prob_{h'}\right] \times LOS_h$.[39] In this expression, *prob* are original choice probabilities based on hospital demand estimation and LOS_h is the patient's length of stay at hospital h as reported by OSHPD. The term in brackets represents the *increased* choice probability of hospital h' while LOS_h represents the extra days available with the removal of hospital h. In the next step, I use OSHPD Discharge and Financial Reports to estimate the average revenue per inpatient day at a hospital for each MDC for a non-ER private patient, and then use it to calculate extra revenues at a hospital. For example, average revenues for a patient diagnosed with MDC category 5 that is admitted through non-ER is calculated as:

$$\text{Avg.Rev./Day} = \frac{\text{Net Revenues from Private Payers}}{\text{Gross Charges for Private Payers}} \times \frac{\text{Total IP Charges for Private-non-ER in MDC5}}{\text{Total IP Days for Private-non-ER in MDC5}}$$

Given the average revenue measure, total extra revenues at a hospital are calculated by multiplying predicted extra days with the average revenues that correspond to that MDC, and then aggregating it to the hospital level. This hospital level measure is the total reimbursements from all insurers the hospital contracts with. Therefore, to break it down to hospital-insurer level, I multiply it with $s_{jh}^{ins-hosp}$ and use this final term in estimation.

The final component of surplus, $p_{hj}D_h(\mathcal{M})$, is the change in revenues of a hospital when it contracts with an insurer. I use the same average revenue measure in lieu of the reimbursement price vector p_{hj} and calculate the change in expected demand for the hospital $D_h(\mathcal{M})$ based on hospital demand estimation. In particular, I start at the individual level and calculate *predDays* as above (by multiplying hospital choice probability with length of stay of each private individual), then predict the revenues from these days by MDC using the average revenue measure, and finally aggregate these revenues to the hospital level. This aggregate measure is again broken into hospital-insurer level using $s_{jh}^{ins-hosp}$. Finally, the left hand side variable, $\Delta_j \Pi_h$, is calculated by subtracting the change in costs discussed above from the total extra revenue generated.

I estimate two specifications of the bargaining model. The first specification is estimated at the hospital-insurer level where the negotiating hospital unit is a hospital. This specification assumes hospitals negotiate with insurers individually and not as systems. Belonging to a hospital system can still improve a hospital's

[39] This expression is calculated at the individual level and then aggregated to hospital-MDC level at each iteration.

bargaining position in this specification through the system membership variable. In the second specification, the negotiating hospital unit is a hospital if the hospital is a member of a non-FLF system or an individual hospital, and a system otherwise. In other words, I only allow FLF-offering systems to negotiate as a system. In this dataset, binary hospital characteristics are calculated as a fraction when the negotiating unit is an FLF-offering system.[40] Hospital and system shares used in HHI are calculated based on hospital visits in that hospital/system and in that HRR. While constructing the components of the bargaining equation, I calculate each variable at the hospital level first, and then aggregate to the system level by summing across member hospitals if the hospital belongs to an FLF-offering system. The disaggregation from system level to system-insurer level variables is again done by using $s_{jh}^{ins-hosp}$, which in these instances represent the share of patients at system h coming from insurer j.

The two specifications represent the two extremes of the health care market I observe in the data. In practice, not all hospitals negotiate individually and independently with insurers, as some systems tie their hospitals together and negotiate as a system. However, it is also true that not all systems try to impose full-line of their products to all insurers they negotiate with. The system level bargaining model in this paper improves upon the previous bargaining estimations in the literature that assume *all* hospital systems negotiate as systems[41] by identifying FLF-offering systems as negotiating units. Nonetheless, while the hospitals in these systems are often tied together, they also negotiate individually with some insurers, which is not captured by the system level estimation.

Results from bargaining estimation are presented in Table 7. The coefficient estimates are similar in terms of sign and significance across two specifications. Hospitals with higher shares have higher bargaining power, as expected. VI hospitals have higher bargaining power compared to their non-VI counterparts. At the individual level specification, the positive impact of being a system member on a hospital's bargaining power is greater in terms of magnitude compared to the system level specification. This is as anticipated because system membership is one of the few variables that capture the advantages of being in a hospital system in this specification that does not force systems to tie their products. Belonging to an FLF-offering system has a negative impact on bargaining power, although this coefficient is not significant in the second specification. This unexpected result might be arising from the fact that increased bargaining power through system membership is already captured by other covariates such as system membership, VI status, and system or

[40]For example, if 2 out of 4 system hospitals are teaching hospitals, the teaching indicator variable for that system is 0.50.
[41]See Gowrisankaran et al. (2015) and Lewis and Pflum (2015).

Table 7: Determination of Bargaining Power

Dep. var.: $\Delta\Pi_h$	(1) Individual Level	(2) System Level
Base bargaining power	0.98***	0.80**
	(0.11)	(0.38)
VI-hospital	0.53***	0.02**
	(0.09)	(0.01)
FLF-hospital	-1.19**	-0.14
	(0.54)	(0.34)
Hospital share	1.28***	0.11**
	(0.47)	(0.05)
Hospital market HHI	-2.78***	0.57
	(0.81)	(1.13)
Predicted days	0.002	0.0003***
	(0.004)	(0.00002)
Teaching hospital	-0.34***	-0.03**
	(0.09)	(0.02)
Rural hospital	-0.13	-0.02
	(0.09)	(0.02)
For-profit hospital	0.02	0.01
	(0.10)	(0.01)
Physician group	0.04	-0.48***
	(3.56)	(0.08)
System member	1.33**	0.14***
	(0.55)	(0.02)
γ^{-1} (x1000)	1.24***	0.83***
	(0.10)	(0.08)
Bargaining Power:		
Mean fitted value	0.69	0.63
Standard deviation	0.19	0.20
N	4936	2163
Adjusted R^2	0.39	0.95

Notes: Results from nonlinear least squares estimation using California data. Individual level sample includes 276 hospitals and 32 insurers, system level sample includes 116 systems/hospitals and 32 insurers. Both specifications include HRR fixed effects. Predicted patient days in thousands. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

hospital share. The bottom part of Table 7 reports the mean fitted values of hospital bargaining power. Like previous papers in the literature, I find that hospitals, on average, have higher bargaining power than insurers in the negotiation process. These results are robust to dropping the VI hospital-insurer pairs from the dataset. These pairs likely do not engage in bargaining since they own one another. I also estimated specifications where I allowed hospital bargaining power to depend on the characteristics of the insurer it contracts with. This approach did not improve the fit of the model and insurer characteristics never proved to be informative in explaining hospital's bargaining power. Given the results in Table 7, I conclude the system level regression better models the market as is, given the better fit and more sensible coefficients such as HHI. However, the individual level regression will be useful in simulating the counterfactual world where all hospitals are negotiating individually and independently.

6 Welfare

Having estimated the demand model and bargaining model parameters, the last step is to analyze the welfare impacts of FLF contracts. In order to assess the welfare implications, I simulate a counterfactual world where FLF contracts are banned, hence I allow FLF-offering system hospitals to negotiate individually with insurers. This simulation of the bargaining game with new players results in new hospital networks offered by insurers. New networks imply new costs, prices, and shares for hospitals and insurers, therefore hospital and insurer profits change. New networks and new prices imply new utility for consumers in the market, hence consumer welfare also changes.

I begin my counterfactual analysis by breaking the existing FLF contracts in the California market. As a result, hospitals that belong to a previously FLF-offering system become independent and bargain as individual entities, not as a system. I use estimates from the individual level bargaining specification to predict new networks as the market no longer has systems that impose their full-line of products while negotiating. Estimates from this specification still allow the previously-FLF hospitals to acquire benefits from being in a system through the system membership variable. Lastly, if an insurer is vertically integrated with a hospital system, I keep those system hospitals in VI insurer's network and construct the hospital network given these filled spots. If the vertically-integrated hospital system contracted with insurers other than its own in my data, I allow these hospitals to negotiate with insurers in the counterfactual world. Given this setup, I follow the steps below to obtain new hospital networks offered by insurers:

1. Re-predict individual hospital choice probabilities by setting FLF indicator to zero in the hospital demand postestimation. Calculate new $predDays$ and $extraPredDays$ at each hospital given the new probabilities.

2. Use the new hospital choice probabilities to re-calculate every element of the bargaining model. In particular, I obtain new values for the hospital level variables $\Delta W_h(\mathcal{M})$, $\Delta C_h(D_h(\mathcal{M}))$, $\Delta R_h(p_{h\mathcal{H}})$, and $p_{h\mathcal{H}}D_h(\mathcal{M})$.

3. Break hospital level variables into hospital-insurer level variables. In the first iteration, I begin by assuming all hospitals contract with all insurers, and do the decomposition using $s_{jh}^{ins-hosp}$ calculated under this assumption.

4. Predict changes in hospital profits, $\Delta_j\Pi_h$, for every hospital-insurer pair by using parameter estimates from the bargaining model by setting FLF indicator to zero in the bargaining model, and using the re-calculated elements of surplus from step 3. Hospital h chooses to sign a contract with insurer j if $\Delta_j\Pi_h > 0$, hence new networks are formed.

Given the new networks, I go back to step 3 and re-calculate hospital shares at a hospital following the share calculation outlined in the appendix that accounts for insurer networks while imposing capacity constraints. I keep iterating using this routine until equilibrium is reached. At this equilibrium, no hospital has an incentive to deviate and change the set of insurers it contracts with. This routine relies on the assumption that if a hospital is willing to join an insurer's network, the insurer will agree to establish a contract. This assumption is supported by both theory[42] and data.[43]

Next, I calculate new premiums given the new insurer networks. Insurers maximize a standard profit function by choosing premiums:

$$\pi_j = (prem_j - C_j \times p_{ip}) \times s_j \times M \tag{36}$$

where M is market size, $C_j = \sum\limits_{h\in\mathcal{H}} \frac{s_h}{\sum\limits_{k\in\mathcal{H}} s_k} \times p_h$ is the average reimbursement per day by insurer j to the set of hospitals $\mathcal{H}$ in its network, and p_{ip} is the number of inpatient days at a state divided by total population.

[42]Capps et al. (2003) present a model of network formation which shows that the profit maximizing strategy for an insurer is to include all the hospitals in the market in its network.

[43]Lewis and Pflum (2015) state that their communications with a former contract negotiator for a major national insurer revealed PPOs' strategies are to include almost every hospital in the market in their network. In their data, the median HMO covers 84% of hospitals in the market. Ho (2009) reports, on average, 87% of hospital-HMO pairs successfully sign a contract. In my data, the median HMO and PPO cover 42% and 60% of the hospitals in the market, respectively. Therefore, I assume both HMOs and PPOs aim to cover a substantial portion of the market where possible.

Maximizing the objective function leads to the following first order condition that determines premiums:

$$s_j + (prem_j - C_j \times p_{ip})\frac{\partial s_j}{\partial prem_j} = 0 \tag{37}$$

Finally, given the new networks and new premiums, I calculate the change in producer surplus and consumer welfare. Producer surplus is the aggregation of all hospital and insurer profits in the market. Hospital profits are calculated as: $\pi_h = (p_h \times p_{ip} \times \sum_{j \in \mathcal{M}} Ms_{jh}) - Cost_h$ where p_h is the average revenue per inpatient day at hospital h, and $Cost_h$ is the predicted cost of the hospital given new predicted days. Insurer profits are calculated using equation (36).

I use compensating variation (CV) to measure the change in consumer welfare when vertical bundling is removed from the market. Compensating variation refers to the amount of money a consumer would need to give up following a change in prices or product quality (hospital networks) in order to reach his pre-change utility level. Following Small and Rosen (1985), the compensating variation for consumer i is given by:

$$CV_i = -\frac{1}{\alpha_i}\left[ln \sum_j exp(V_{ij}^{post}) - ln \sum_j exp(V_{ij}^{pre})\right] \tag{38}$$

where the superscripts *post* and *pre* refer to the removal and presence of FLF contracts, respectively. $-\alpha_i = -(\beta_2 + \gamma_2 v_{i2})$ is the negative of the premium coefficient and j still represents an insurer. V is the observed portion of utility defined as:

$$V_{ij} = \xi_j + x_j\hat{\phi} + \hat{\beta}_1 EU_j + \hat{\beta}_2 prem_j + \hat{\gamma}_1 \nu_{i1} EU_j(H_j) + \hat{\gamma}_2 \nu_{i2} prem_j \tag{39}$$

Compensating variation is then the market size times the integral of compensating variation over the distribution of ν as given by:

$$CV = M \int CV_i dP_\nu(\nu) \tag{40}$$

Applying this to the random-coefficients model, I calculate the compensating variation by simulation. In particular, I calculate compensating variation for each draw of ν, and then take the average across these ns draws to obtain:

$$CV = M\frac{1}{ns}\sum_{i=1}^{ns} CV_i \tag{41}$$

Counterfactual results using California data[44] are reported in Table 8. I present results for the entire sample, previously FLF entities, and previously non-FLF entities. In the first panel, percentages represent average changes compared to FLF contracts being present in the market. In the second panel, percentages represent the split within their own categories defined by FLF status and entity type.

I find that consumer welfare decreases by $5.9 billion upon removal of FLF contracts from the market. The decline in consumer welfare is a combination of increase in premiums and decrease in expected utility. Majority of insurers increase their network size when I ban FLF contracts, which leads to an increase in premiums. Average increase in network size is 41%, which leads to an average increase in premiums by 34%. Some insurers also increase premiums because they now contract with more expensive hospitals, which increases their costs. While the expected utility measure increases for some insurers who expand their networks, it decreases for others, which contributes to the decline in welfare. Expected utility decreases for insurers that shrink their networks, as expected. Decrease in expected utility among the insurers that increase network size stems from the composition of their networks. While these insurers still include a few hospitals from previously-FLF-offering systems, they replace the block of FLF system hospitals they were including before with individual hospitals that are less equipped and offer fewer services, which leads to a decline in expected utility. Switch to cheaper individual hospitals also prevents a drastic increase in premiums.

The finding that FLF contracts are welfare improving for consumers is consistent with the conclusion from the reduced-form analysis, however, the predicted source is not. Reduced-form regressions showed that FLF insurers offer larger networks and they include more hospitals from all categories. The counterfactual simulation here demonstrates that network size increases when I remove FLF contracts from the market, even above the original size of FLF-insurers' networks in most cases. Therefore, FLF contracts do not increase consumer welfare by increasing network size, rather they contain network size and premiums which benefits consumers.

Producer surplus decreases by $10 billion when I remove FLF contracts from the market. The overall decline in producer surplus originates from dominating hospital losses. In the insurer market, the loss of $1.1 billion is offset by $11.1 billion increase in profits. The majority of increase in profits comes from insurers who previously accepted FLF contracts. This is as anticipated, as these insurers now have an expanded choice set and their network slots are not dedicated to an entire system. Even though insurers are not the decision

[44] Among the 32 insurers in my data, 29 accept FLF contracts and 6 are vertically integrated with hospital systems. Among the 276 hospitals I use, 185 belong to systems that offer FLF contracts. The average network size is 154 and ranges between 3 and 248.

makers in network formation, they still have more hospital options to pair with in this counterfactual world. New networks also increase profits of all non-FLF insurers in the market. 35% of the FLF insurers in my data lose profits as their shares decline in response to changes in premiums and expected utility. In the hospital market, 61% of all hospitals lose profits, while 39% gain. The majority of loss comes from hospitals who belong to FLF-offering systems, these hospitals lose $50 billion in profits. This is a sensible result because offering FLF contracts must have been the profitable choice for them to begin with.[45] Yet, there are some FLF offering systems in the market who benefit from the new market structure. These hospitals gain from increased market share that results from contracting with more insurers individually. 64% of non-FLF hospitals lose profits and their loss of $28.4 billion offsets the gain of $17 billion by the remaining non-FLF hospitals. These changes are mostly due to the changes in shares of individual hospitals. Breaking hospital systems increases the number of competitors in the market for individual hospitals, and they lose some share to these "new" players. Switch of insurers to other individual hospitals is the source of increasing profits in the non-FLF hospital category.

7 Conclusion

This paper investigates the effects of vertical bundling in supply chain on consumer welfare and producer surplus. I focus on the health care industry in the United States, and analyze FLF contracts imposed by hospital systems in the negotiation process with insurers. Economic theory suggests such contracts might increase welfare through their impact on efficiency, but they might also adversely affect welfare if they are used to gain leverage over the upstream competitors.

Results from my reduced-form estimations show that insurers that accept all members of at least one hospital system in the market are likely to offer larger hospital networks. Moreover, FLF-accepting insurers do not include FLF-offering system hospitals at the expense of their competitors. These insurers are likely to include more individual hospitals, non-FLF system member hospitals, and even rival FLF system member hospitals in their networks, compared to insurers who do not take FLF contracts. I also find that the premiums of the two kinds of insurers do not differ significantly, however this result is obtained using premiums data at the national level, not at the market level.

[45]This result is also consistent with the conclusion in Ho et al. (2012a). They find that offering FLF contracts is the profitable choice for the upstream companies that choose to offer them.

Table 8: Counterfactual Results: Removal of FLF Contracts

	All	FLF	Non-FLF
Δ CS: $ -5.9b			
Premiums	34%	39%	28%
$ CS lost	$ -7.7b		
Network Size	41%	51%	15%
$ CS gained	$ 1.8b		
Δ PS: $ -10b			
Percent of hospitals at loss	61%	59%	64%
Hospital Π lost	$ -77.9b	$ -49.5b	$ -28.4b
Percent of hospitals at gain	39%	41%	36%
Hospital Π gained	$ 57.7b	$ 40.7b	$ 17b
Percent of insurers at loss	31%	35%	-
Insurer Π lost	$ -1.1b	$ -1.1b	-
Percent of insurers at gain	69%	65%	100%
Insurer Π gained	$ 11.1b	$ 10.9b	$ 222m

Notes: Results from counterfactual simulation where FLF contracts are removed from the market.

If FLF contracts lead to increased consumer choice at the same price, they should increase consumer welfare. To investigate whether this is the case, and to quantify the change in welfare, I structurally model the market and simulate a counterfactual world absent of FLF contracts. I find that FLF contracts benefit consumers, but not by expanding their choice sets. In fact, insurers are inclined to offer even larger networks in the absence of FLF contracts, which leads to higher premiums and harms consumers. Upon removal of FLF contracts from the market, consumer welfare drops by $5.9 billion, producer surplus drops by $10 billion a year. While the results are mixed for individual hospitals and insurers, majority of the loss comes from the hospital sector. Many previously-FLF-offering system hospitals and individual hospitals lose profits as they lose shares to the new competitors in the market. Removal of vertical restraints enable insurers to contract with hospitals from a less restrictive set, and as a result, they increase their network size, premiums, and profits.

These results are important given the increasing consolidation in health care markets. Previous literature has shown horizontal consolidation in the upstream market is likely to decrease consumer welfare through increased bargaining power for hospital systems and increased hospital prices. In this paper, I show that hospital system bundling might have a positive effect on consumer welfare by containing insurer network size and premiums. My results are partial, as they do not account for change in hospital prices as a result of de-bundling, which would be another source of change in welfare. Yet, the results in this paper imply the impact of horizontal consolidation on consumer welfare does not necessarily need to be negative. Future research on this subject would ideally use transaction prices between hospitals and insurers to identify possible discounts offered for bundles, and incorporate these prices into the framework presented here.

8 Appendix

8.1 Hospital and System Distribution by State

Following figures replicate the figures in section 2 using the strictest definition of FLF.

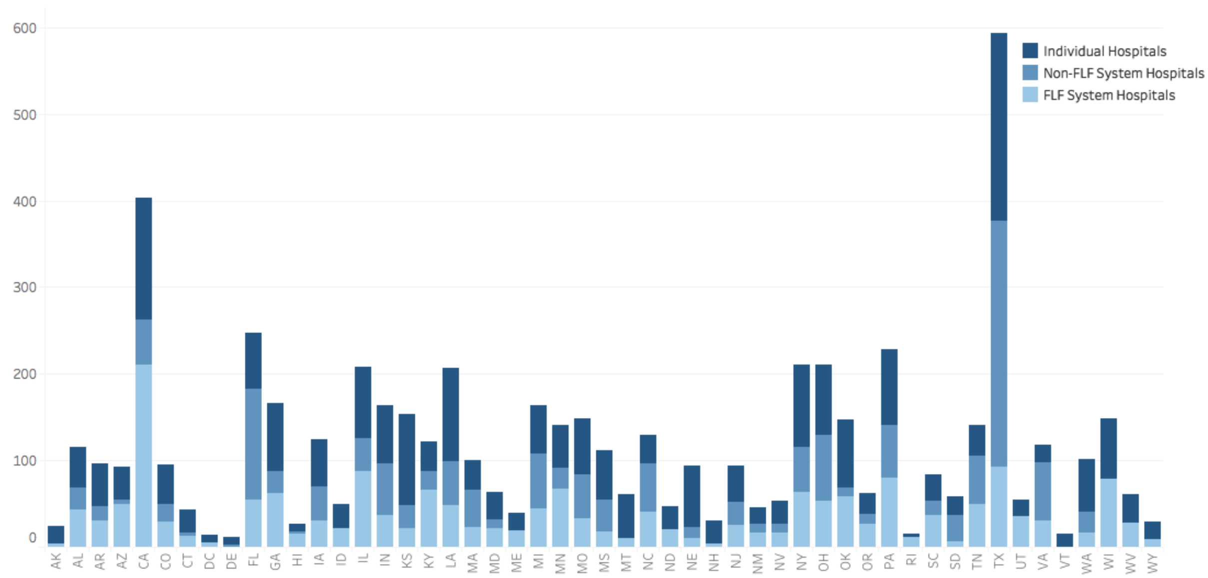

Figure A1: Number of individual, non-FLF system member, and FLF system member hospitals by state

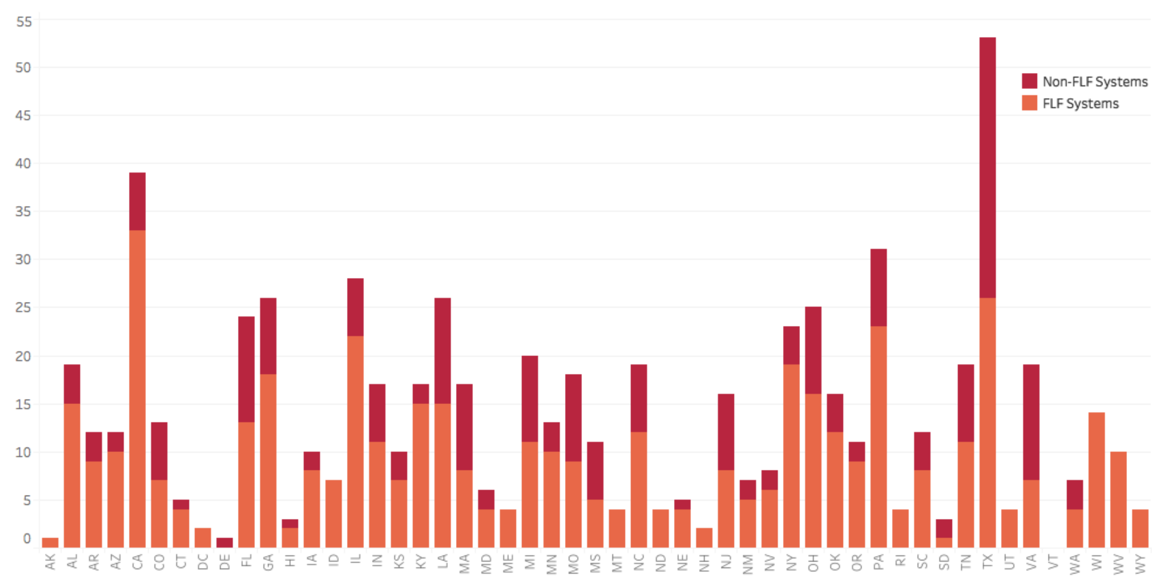

Figure A2: Number of non-FLF and FLF-offering hospital systems by state

8.2 Reduced-Form Analysis - Robustness

In Table A1, I report results from robustness checks for the reduced-form estimations in section 3. Only the coefficient in front of the covariate of interest, FLF-insurer, is reported for each regression. The first row replicates the coefficients reported in the paper where the least restrictive definition of FLF was used. As a robustness check, I estimate the same specifications using two alternative measures of FLF: one where a hospital system is considered as an FLF-offering system if 90% of its hospitals were included in at least one insurer's network, and another where all (100%) member hospitals are included in at least one insurer's network. FLF statuses of insurers are defined analogously. In the second and third rows, I report the coefficient of interest obtained by using 90% and 100% measures, respectively. In the fourth row, results from main estimation with added insurer fixed effects are reported. Results in the paper are robust to use of the two other FLF measures as well as inclusion of insurer fixed effects, as reported Table A1.

Table A1: Robustness of Reduced-form Results

	Efficiency	Market Coverage		Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
	ln Premium	Network Size	FLF hospitals	Individual	Non-FLF	Rival FLF
FLF: 80% coverage	0.08	48.18***	25.56***	18.47***	4.15***	1.88***
	(0.09)	(14.46)	(6.84)	(5.35)	(0.91)	(0.10)
FLF: 90% coverage	0.13	48.10***	20.88***	18.42***	8.80***	1.55***
	(0.09)	(13.77)	(4.83)	(5.10)	(1.64)	(0.09)
FLF: 100% coverage	0.12	48.70***	17.24***	18.56***	12.90***	1.17***
	(0.09)	(13.89)	(3.22)	(5.12)	(2.48)	(0.07)
Insurer FE	-	34.64**	18.61**	14.50***	1.53*	1.71***
		(13.61)	(7.43)	(5.55)	(0.82)	(0.16)

Notes: Results from ordinary least squares estimation. Coefficient in front of FLF-insurer reported for each specification. *** statistically significant at 1%, ** statistically significant at 5%, * statistically significant at 10%.

8.3 Share of patients at a hospital from an insurer

The share calculation is done based on hospital shares, insurer shares, and capacity constraints. Let M be market size, cc_h be the capacity constraint of hospital h, and s_h and s_j represent market shares of hospital h and insurer j, respectively. Capacity constraints are defined by the number of beds at a hospital, and hospitals are assumed to operate at full capacity when the constraints are imposed. To begin with, I allocate patients to hospitals based on hospital networks offered by insurers, hospital shares, and insurer shares. Share of patients enrolled in plan j that visit hospital h is calculated as:

$$s_{jh} = s_j \times \frac{s_h}{\sum\limits_{h \in K} s_h} \tag{42}$$

where K is the set of hospitals insurer j contracts with. However, when the allocation is done this way, some hospitals exceed their capacity limits. If this is the case, I remove excess patients from that hospital and re-allocate them to remaining hospitals in the market who have not reached their capacity constraints at this stage, based on shares s_{jh}. Following this re-allocation, I calculate shares $s_{jh}^{ins-hosp}$.

Formally, if hospital h exceeds its capacity, then I remove E_j many patients from insurer j's allocated patients to hospital h, where E_j is given by:

$$E_j = \left[\left(M \times \sum_{j \in H} s_{jh}\right) - cc_h\right] \times \frac{s_{jh}}{\sum\limits_{j \in R} s_{jh}} \tag{43}$$

In this equation, H is the set of insurers hospital h contracts with and R is the set of insurers contracted with hospital h who will re-allocate a fraction of their patients to other hospitals.[46] First term in brackets is the number of excess patients at hospital h, whereas the second term represents the share of insurer j among insurers who will re-allocate their patients from hospital h. Re-allocation of these removed patients to other hospitals is done based on insurer shares at the destination hospital. For any hospital h' that is short of its capacity, I first determine the number of patients it can accept, and then re-allocate patients to h' based on their initial shares at h'. Formally, I assume T_j many patients will be added to hospital h''s network from insurer j as a result of removing excess capacity from hospital h, where T_j is defined as:

$$T_j = \left[cc_{h'} - \left(M \times \sum_{j \in H'} s_{jh'}\right)\right] \times \frac{s_{jh'}}{\sum\limits_{j \in L} s_{jh'}} \tag{44}$$

Here, the first term in the brackets represents the number of patients hospital h' can accept, and the second term represents the share of insurer j among other insurers who contracted with hospital h' and with at least one other hospital that exceeds its capacity in the previous step. Given this final allocation, I calculate $s_{jh}^{ins-hosp} = \frac{n_{jh}}{\sum\limits_{j \in H} n_{jh}}$ where n_{jh} is the number of patients allocated to hospital h from insurer j.

[46] Insurers in set R are insurers who contracted with hospital h and at least with one other hospital that is short in capacity.

8.4 Hospital Demand and Cost Estimations

The full set of parameter estimates from the hospital demand and hospital cost models are reported in Table A2 and Table A3, respectively.

Table A2: Hospital Demand Estimation

Variable	Coefficient	Variable	Coefficient
Distance (miles)	-0.03*** (0.0001)	Neonatal intensive care	0.12*** (0.007)
Distance squared	0.00002*** (0.0000001)	Neonatal intermediate care	0.23*** (0.006)
VI hospital	0.05*** (0.005)	Pediatric intensive care	0.02*** (0.004)
VI x Distance	-0.003*** (0.00009)	Burn care	-0.18*** (0.005)
Age (0-17) x Distance	-0.03*** (0.0002)	Physical rehabilitation care	-0.19*** (0.003)
Age (18-34) x Distance	-0.02*** (0.0002)	Alcohol/drug abuse care	0.22*** (0.004)
Age (35-44) x Distance	-0.01*** (0.0002)	Psychiatric care	-0.14*** (0.003)
Age (45-54) x Distance	0.0008*** (0.0002)	Skilled nursing care	-0.20*** (0.005)
Female x Distance	-0.01*** (0.0001)	Intermediate nursing care	-0.04*** (0.006)
For-profit hospital	-0.40*** (0.005)	Acute long term care	-0.32*** (0.008)
Nurses per bed	0.22*** (0.002)	Alzheimer center	0.32*** (0.005)
Teaching hospital	0.06*** (0.005)	Arthritis treatment center	0.04*** (0.005)
Bed size (6-24)	-2.81*** (0.03)	Birthing room	-0.02 (0.02)
Bed size (25-49)	-2.40*** (0.01)	Breast cancer screening/mammograms	-0.08*** (0.006)
Bed size (50-99)	-1.48*** (0.008)	Adult cardiology services	-0.55*** (0.007)
Bed size (100-199)	-0.77*** (0.006)	Diagnostic catheterization	-0.07*** (0.006)
Bed size (200-299)	-0.41*** (0.005)	Interventional cardiac catheterization	0.12*** (0.006)
Bed size (300-399)	-0.20*** (0.005)	Adult cardiac surgery	0.10*** (0.004)
Bed size (400-499)	0.01** (0.005)	Cardiac rehabilitation	0.06*** (0.003)
Medical/surgical care	0.26*** (0.02)	Chemotherapy	0.17*** (0.007)
Obstetrics care	-0.24*** (0.02)	Computer assisted orthopedic surgery	0.10*** (0.003)
Medical/surgical intensive care	-0.16*** (0.01)	Optical colonoscopy	-0.17*** (0.005)
Cardiac intensive care	-0.11*** (0.004)	Endoscopic ultrasound	-0.11*** (0.004)

Table A2: Hospital Demand Estimation - continued

Variable	Coefficient	Variable	Coefficient
Ablation of Barrett's esophagus	-0.19*** (0.003)	Full-field digital mammography	0.08*** (0.006)
Endoscopic retrograde cholangiopancreatography (ERCP)	-0.14*** (0.006)	Magnetic resonance imaging (MRI)	-0.21*** (0.007)
Extracorporeal shock waved lithotripter (ERCP)	-0.06*** (0.004)	Intraoperative magnetic resonance imaging	-0.11*** (0.004)
Fertility clinic	0.02*** (0.006)	Magnetoencephalography (MEG)	-0.16*** (0.004)
Geriatric services	0.18*** (0.004)	Multislice spiral computed tomography <64 slice	-0.09*** (0.005)
Health screenings	-0.32*** (0.007)	Multislice spiral computed tomography 64+ slice	0.07*** (0.005)
Hemodialysis	-0.20*** (0.004)	Positron emission tomography (PET)	-0.03*** (0.004)
HIV-AIDS services	0.27*** (0.004)	PET/CT	0.02*** (0.005)
Immunization program	0.05*** (0.004)	Single photon emission computerized tomography (SPECT)	-0.05*** (0.004)
Indigent care clinic	-0.06*** (0.004)	Ultrasound	0.35*** (0.02)
Linguistic/translation services	0.04*** (0.004)	Image-guided radiation therapy	0.20*** (0.007)
Neurological services	0.03*** (0.007)	Intensity-modulated radiation therapy (IMRT)	-0.34*** (0.009)
Oncology services	0.14*** (0.009)	Proton beam therapy	-0.22*** (0.009)
Orthopedic services	0.02** (0.01)	Shaped beam radiation system	0.22*** (0.008)
Pain management program	0.15*** (0.005)	Stereotactic radiosurgery	-0.02*** (0.004)
Palliative care program	-0.04*** (0.004)	Robotic surgery	0.41*** (0.004)
Inpatient palliative care unit	0.10*** (0.003)	Sleep center	0.13*** (0.003)
Electrodiagnostic services	0.11*** (0.003)	Sports medicine	-0.04*** (0.003)
Physical rehabilitation outpatient services	-0.09*** (0.005)	Tobacco treatment services	0.16*** (0.004)
Psychiatric geriatric services	-0.11*** (0.004)	Bone marrow transplant services	0.22*** (0.006)
Computed-tomography (CT) scanner	-0.70*** (0.02)	Heart transplant	-0.25*** (0.006)
Diagnostic radioisotope facility	0.05*** (0.006)	Kidney transplant	0.006 (0.006)
Electron Bean Computed Tomography	0.02*** (0.004)	Liver transplant	-0.11*** (0.007)

Table A2: Hospital Demand Estimation - continued

Variable	Coefficient	Variable	Coefficient
Lung transplant	0.11*** (0.007)	Neonatal intermediate care x Female	-0.03*** (0.006)
Tissue transplant	0.01*** (0.004)	Burn care x Burns	3.75*** (0.13)
Virtual colonoscopy	0.20*** (0.003)	Alcohol/drug abuse care x Alcohol/drug induced mental disorders	2.94*** (0.03)
Women's health center	-0.03*** (0.007)	Psychiatric care x Mental diseases and disorders	1.87*** (0.02)
Adult cardiology services x Age (35-54)	0.61*** (0.007)	Birthing room x Pregnancy, childbirth and puerperium	0.43*** (0.02)
Acute long term care x Age (45-54)	0.26*** (0.01)	Birthing room x Newborn and other neonates	0.33*** (0.02)
Arthritis treatment center x Age (45-54)	0.12*** (0.008)	Birthing room x Female	0.15*** (0.02)
Medical/surgical care x Circulatory system	-0.69*** (0.05)	Blood donor center x Circulatory system	0.19*** (0.02)
Medical/surgical care x Hepatobiliary and pancreas	0.76*** (0.06)	Blood donor center x Blood and blood forming organ disorders	0.71*** (0.05)
Medical/surgical care x Skin, subcutaneous tissue and breast	0.73*** (0.05)	Breast cancer screening/mammograms x Skin, subcutaneous tissue and breast	0.40*** (0.05)
Medical/surgical care x Male reproductive system	0.43*** (0.08)	Adult cardiology services x Circulatory system	0.17*** (0.05)
Medical/surgical care x Female reproductive system	0.85*** (0.03)	Diagnostic catheterization x Kidney and urinary tract	0.38*** (0.03)
Medical/surgical care x Pregnancy, childbirth and puerperium	-2.58*** (0.05)	Interventional cardiac catheterization x Circulatory system	0.58*** (0.04)
Medical/surgical care x Multiple significant trauma	1.16*** (0.05)	Adult cardiac surgery x Circulatory system	1.30*** (0.02)
Obstetrics care x Pregnancy, childbirth and puerperium	4.58*** (0.05)	Cardiac rehabilitation x Circulatory system	0.01 (0.02)
Obstetrics care x Newborn and other neonates	1.89*** (0.02)	Chemotherapy x Ear, nose, mouth and throat	1.36*** (0.10)
Obstetrics care x Female	-0.05** (0.02)	Chemotherapy x Respiratory system	0.11** (0.05)
Cardiac intensive care x Circulatory system	0.03 (0.02)	Chemotherapy x Digestive system	0.15*** (0.03)
Neonatal intensive care x Pregnancy, childbirth and puerperium	0.12*** (0.008)	Chemotherapy x Hepatobiliary and pancreas	0.31*** (0.06)
Neonatal intensive care x Newborn and other neonates	0.15*** (0.007)	Chemotherapy x Skin, subcutaneous tissue and breast	0.39*** (0.06)
Neonatal intensive care x Female	0.06*** (0.007)	Chemotherapy x Male reproductive system	0.59*** (0.09)
Neonatal intermediate care x Pregnancy, childbirth and puerperium	-0.20*** (0.007)	Chemotherapy x Female reproductive system	0.14*** (0.03)
Neonatal intermediate care x Newborn and other neonates	-0.17*** (0.007)	Chemotherapy x Blood disorders	0.79*** (0.11)

Table A2: Hospital Demand Estimation - continued

Variable	Coefficient	Variable	Coefficient
Optical colonoscopy x Digestive system	0.39*** (0.02)	Diagnostic radioisotope facility x Circulatory system	0.24*** (0.03)
Endoscopic ultrasound x Digestive system	0.15*** (0.02)	Full-field digital mammography x Skin, subcutaneous tissue and breast	-0.06 (0.04)
Ablation of Barrett's esophagus x Digestive system	-0.04** (0.01)	MRI x Nervous system	0.50*** (0.03)
ERCP x Digestive system	0.55*** (0.02)	MRI x Respiratory system	0.34*** (0.04)
ERCP x Hepatobiliary and pancreas	0.73*** (0.04)	MRI x Circulatory system	0.04 (0.03)
ESWL x Hepatobiliary and pancreas	0.08*** (0.02)	MRI x Digestive system	0.46*** (0.02)
ESWL x Kidney and urinary tract	0.30*** (0.02)	MRI x Male reproductive system	0.63*** (0.07)
Fertility clinic x Female reproductive system	0.14*** (0.02)	Multislice spiral computed tomography <64 slice x Nervous system	0.14*** (0.02)
Fertility clinic x Female	-0.05*** (0.006)	Multislice spiral computed tomography <64 slice x Respiratory system	0.21*** (0.03)
Hemodialysis x Kidney and urinary tract	0.34*** (0.03)	Multislice spiral computed tomography <64 slice x Circulatory system	-0.30*** (0.02)
HIV-AIDS services x Infectious and parasitic DD	0.60*** (0.03)	Multislice spiral computed tomography 64+ slice x Nervous system	0.18*** (0.03)
Neurological services x Nervous system	0.92*** (0.03)	Multislice spiral computed tomography 64+ slice x Respiratory system	0.21*** (0.03)
Oncology services x Ear, nose mouth and throat	0.09 (0.10)	Multislice spiral computed tomography 64+ slice x Circulatory system	-0.11*** (0.03)
Oncology services x Respiratory system	-0.16*** (0.05)	PET/CT x Nervous system	0.35*** (0.01)
Oncology services x Digestive system	-0.32*** (0.03)	PET/CT x Respiratory system	0.24*** (0.02)
Oncology services x Hepatobiliary and pancreas	-0.41*** (0.07)	PET/CT x Circulatory system	0.07*** (0.02)
Oncology services x Skin, subcutaneous tissue and breast	-0.41** (0.06)	PET/CT x Skin, subcutaneous tissue and breast	0.12** (0.02)
Oncology services x Male reproductive system	-0.18* (0.10)	Ultrasound x Pregnancy, childbirth and puerperium	-0.57*** (0.02)
Oncology services x Female reproductive system	-0.07 (0.04)	Ultrasound x Female	-0.04*** (0.01)
Oncology services x Blood disorders	0.76*** (0.11)	Heart transplant x Circulatory system	0.45*** (0.02)
Psychiatric geriatric services x Mental diseases and disorders	0.10*** (0.02)	Kidney transplant x Kidney and urinary tract	0.88*** (0.02)
Diagnostic radioisotope facility x Ear, nose, mouth and throat	0.34*** (0.06)	Liver transplant x Digestive system	0.46*** (0.02)
Diagnostic radioisotope facility x Respiratory system	-0.06*** (0.03)	Lung transplant x Respiratory system	0.51*** (0.03)

Table A2: Hospital Demand Estimation - continued

Variable	Coefficient	Variable	Coefficient
Tissue transplant	0.20***	Women's health center	0.36***
x Skin, subcutaneous tissue and breast	(0.02)	x Female reproductive system	(0.02)
Virtual colonoscopy	-0.07***	Women's health center	0.06***
x Digestive system	(0.01)	x Female	(0.008)
FLF hospital	0.04***		
	(0.03)		

Notes: Results from maximum likelihood estimation. Standard errors in parentheses. Omitted bed size category is 500+ beds, omitted age category is 45-54. Fixed effects included for hospitals missing AHA data. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

Table A3: Cost Function Estimates

	Coef.	× For-Profit Coef.	× Govt. Coef.	× Rural Coef.	× Teaching Coef.	× VI Coef.	× FLF Coef.
Percent ER	0.40**	-0.13	0.10	0.48**	-0.29	-0.52***	-0.07
	(0.17)	(0.15)	(0.23)	(0.22)	(0.27)	(0.20)	(0.16)
Percent Medicare	-0.35	0.18	-0.60	-0.99**	1.60	1.43	-0.09
	(0.52)	(0.46)	(0.62)	(0.44)	(1.13)	(0.97)	(0.51)
Other OP	0.54**	-0.75***	-0.55*	-0.02	0.53	-0.27	-0.27
	(0.24)	(0.26)	(0.33)	(0.24)	(0.63)	(0.39)	(0.21)
Other OP^2	-0.004	0.003	0.005	0.01	-0.04**	-0.007	0.006
	(0.006)	(0.006)	(0.01)	(0.006)	(0.02)	(0.02)	(0.004)
Medicare OP	-0.45*	0.30	0.48*	-0.06	0.24	0.62	0.23
	(0.24)	(0.25)	(0.29)	(0.25)	(0.84)	(0.38)	(0.24)
Medicare OP^2	0.007	-0.004	-0.01	0.02***	-0.003	-0.04**	-0.005
	(0.005)	(0.006)	(0.009)	(0.008)	(0.03)	(0.02)	(0.006)
Medicare IP × Private IP	0.005	0.02	0.006	-0.003	0.02	-0.03	-0.0002
	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
All IP × Other OP	-0.04*	0.07***	0.04	-0.02	0.02	0.04	0.02
	(0.02)	(0.02)	(0.03)	(0.02)	(0.06)	(0.04)	(0.02)
Other IP × Medicare IP	-0.02	-0.06**	-0.09*	-0.07*	-0.15*	-0.05	-0.02
	(0.02)	(0.02)	(0.05)	(0.03)	(0.09)	(0.09)	(0.03)
Other IP × Private IP	-0.01	0.02**	0.02**	0.01	0.0003	0.04**	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
All IP × Medicare OP	0.04	-0.02	-0.03	-0.03	-0.02	0.005	-0.02
	(0.02)	(0.03)	(0.03)	(0.02)	(0.07)	(0.04)	(0.03)
All IP × Private OP	0.005	-0.002	0.002	0.006	-0.007**	-0.01***	0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Private FFS OP × Other IP	-0.01	0.008	-0.01	0.01	0.03	-0.02	0.008
	(0.01)	(0.008)	(0.02)	(0.01)	(0.02)	(0.02)	(0.009)
Other IP	0.19	0.23	0.55*	-0.38*	0.44	0.08	0.33
	(0.27)	(0.26)	(0.30)	(0.22)	(0.59)	(0.44)	(0.24)
Other IP^2	0.01	0.004	-0.002	0.04*	0.05	0.03	-0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.04)	(0.02)
Medicare IP × Prvt FFS OP	-0.01	0.0009	-0.008	0.02	-0.07	0.01	-0.004
	(0.01)	(0.02)	(0.01)	(0.01)	(0.04)	(0.02)	(0.01)
Private FFS OP	0.18*	-0.08	0.11	-0.32***	0.44	0.07	0.02
	(0.11)	(0.14)	(0.14)	(0.11)	(0.36)	(0.14)	(0.10)
Private FFS OP^2	0.002	-0.001	0.003	0.003	-0.00003	0.002	-0.006
	(0.003)	(0.004)	(0.004)	(0.003)	(0.007)	(0.008)	(0.004)
Medicare IP	-0.45*	0.42	0.77	-0.41	-0.11	-0.45	-0.55*
	(0.27)	(0.34)	(0.33)	(0.37)	(0.61)	(0.43)	(0.28)
Medicare IP^2	0.02*	-0.003	0.01	0.04***	0.10*	0.07	-0.004
	(0.01)	(0.004)	(0.02)	(0.01)	(0.06)	(0.05)	(0.01)
Fixed Assets	0.02	0.23	-0.35	-0.17	2.16**	1.86**	-0.17
	(0.22)	(0.28)	(0.27)	(0.22)	(0.84)	(0.76)	(0.23)
Fixed $Assets^2$	0.007	-0.009	-0.01	0.002	0.02	-0.05*	0.0007
	(0.008)	(0.009)	(0.01)	(0.008)	(0.02)	(0.02)	(0.008)
Number of Beds	-1.95***	1.90**	1.56*	1.27*	1.35	1.13	-0.76
	(0.61)	(0.94)	(0.82)	(0.68)	(2.60)	(1.25)	(0.60)

Table A3: Cost Function Estimates - continued

	Coef.	× For-Profit Coef.	× Govt. Coef.	× Rural Coef.	× Teaching Coef.	× VI Coef.	× FLF Coef.
Number of Beds^2	-0.13***	0.11**	0.10**	0.08*	0.09	0.01	0.03
	(0.03)	(0.05)	(0.05)	(0.04)	(0.13)	(0.07)	(0.03)
Fixed Assets × Beds	-0.03	-0.04**	-0.01	0.007	0.08	-0.04	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.10)	(0.06)	(0.02)
RN Hours	1.12**	0.32	-1.18**	0.61	-2.87**	-0.90	-0.54
	(0.44)	(0.80)	(0.46)	(0.41)	(1.11)	(0.86)	(0.39)
RN Hours^2	-0.04**	-0.006	0.05**	-0.02	0.11**	0.03	0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)
RN Hours × Staff Hours	-0.05***	0.01	0.05**	-0.009	0.004	0.03	0.03**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)
Empl Hrs × Beds	0.27***	-0.16*	-0.17**	-0.15**	-0.28	-0.04	-0.07
	(0.06)	(0.09)	(0.08)	(0.07)	(0.19)	(0.12)	(0.06)
Empl Hrs × Private IP	0.005	-0.005	-0.001	-0.002	0.003	0.005	-0.003
	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.006)	(0.003)
Empl Hrs × Medicare IP	0.03***	-0.005	-0.002	0.04**	-0.01	-0.05*	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)
Empl Hrs × Fixed Assets	-0.007	0.02	-0.02	0.02	0.08	-0.01	-0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.05)	(0.03)	(0.02)
Private IP	-0.04	-0.18	-0.11	0.05	-0.06	0.03	0.09
	(0.13)	(0.13)	(0.13)	(0.09)	(0.22)	(0.11)	(0.12)
Private IP^2	0.007***	-0.01**	-0.01***	-0.009**	-0.01	-0.01*	0.002
	(0.003)	(0.006)	(0.003)	(0.004)	(0.008)	(0.006)	(0.004)

Notes: Results from ordinary least squares estimation. Clustered standard errors (at the hospital level) in parentheses. All outputs and inputs are in logs. ER is emergency room visits, OP is outpatient visits, IP is inpatient days, FFS is fee-for-service, Empl Hrs is employee hours, RN is registered nurses. Specification includes hospital fixed effects and a time trend. R^2 is above 0.99. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

8.5 Bargaining Estimation - Robustness

In Table A4, I report results from system level bargaining estimation using data and variables created based on different definitions of FLF. First column replicates the system level estimation results reported in the paper. These results are robust to different definitions of FLF, as reported in second and third columns of Table A4.

Table A4: Bargaining Estimation - Robustness

FLF:	80% coverage	90% coverage	100% coverage
Base bargaining power	0.80**	0.98	0.86*
	(0.38)	(0.65)	(0.49)
VI-hospital	0.02**	0.06***	0.04***
	(0.01)	(0.00002)	(0.01)
FLF-hospital	-0.14	-0.54***	-0.03*
	(0.34)	(0.02)	(0.02)
Hospital share	0.11**	0.08	0.13**
	(0.05)	(0.06)	(0.06)
Hospital market HHI	0.57	0.06	0.41
	(1.13)	(1.94)	(1.47)
Predicted days	0.0003***	0.0003***	0.0002***
	(0.00002)	(0.00002)	(0.00002)
Teaching hospital	-0.03**	-0.09***	-0.05***
	(0.02)	(0.02)	(0.02)
Rural hospital	-0.02	-0.03*	-0.03*
	(0.02)	(0.02)	(0.02)
For-profit hospital	0.01	0.01	0.02**
	(0.01)	(0.01)	(0.01)
Physician group	-0.48***	-0.56***	-0.56***
	(0.08)	(0.09)	(0.10)
System member	0.14***	0.54***	0.03*
	(0.02)	(0.03)	(0.02)
γ^{-1} (x1000)	0.83***	0.84***	0.77***
	(0.08)	(0.08)	(0.08)

Notes: Results from nonlinear least squares estimation of system level bargaining equation using California data. All specifications include HRR fixed effects. Predicted patient days in thousands. *** statistically significant at 1% level, ** statistically significant at 5% level, * statistically significant at 10% level.

9 References

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