NBER WORKING PAPER SERIES

INSURER COMPETITION AND NEGOTIATED HOSPITAL PRICES

Kate Ho
Robin S. Lee

Working Paper 19401
http://www.nber.org/papers/w19401

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2013

We thank Patricia Foo for exceptional research assistance; Allan Collard-Wexler, Leemore Dafny, and David Dranove for suggestions; and seminar participants at Columbia, the FTC, Harvard, Johns Hopkins, Kellogg, LSE, NBER Summer Institute, Northwestern, NYU, and SMU for helpful comments. We acknowledge support from the NYU Stern Center for Global Economy and Business. The authors have no other outside sources of funding and no relevant or material outside financial relationships that relate to the research described in this paper. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Insurer Competition and Negotiated Hospital Prices
Kate Ho and Robin S. Lee
NBER Working Paper No. 19401
September 2013
JEL No. I11,L13,L40

ABSTRACT

We examine the impact of increased health insurer competition on negotiated hospital prices. Insurer competition can lead to lower premiums and reduced industry surplus, thereby depressing hospital prices; however, hospitals may also leverage fiercer insurer competition when bargaining in order to negotiate higher prices. We rely on a theoretical bargaining model to derive a regression equation relating negotiated prices to the degree of insurer competition, and use the presence of Kaiser Permanente in a hospital's market as a measure of insurer competition. We estimate a model of consumer demand for hospitals and use it to derive many of the other independent variables specified in the regression equation. Leveraging a unique dataset on negotiated prices between hospitals and commercial insurers in California in 2004, we find that increased insurer competition reduces hospital prices on average, but has a positive and empirically meaningful effect on the prices of attractive and high utility generating hospitals. This heterogeneous effect across hospitals—which has not been emphasized in the recent literature on hospital-insurer bargaining—provides incentives for hospital investment and consolidation, and implies that hospital market power can lead to high input prices even in markets where many insurers are present.

Kate Ho
Columbia University
Department of Economics
1133 International Affairs Building
420 West 118th Street
New York, NY 10027
and NBER
kh2214@columbia.edu

Robin S. Lee
NYU Stern, Department of Economics
44 West 4th Street, KMC 7-78
New York, NY 10012
rslee@stern.nyu.edu

Insurer Competition and Negotiated Hospital Prices*

Kate Ho† Robin S. Lee‡

August 2013

Abstract

We examine the impact of increased health insurer competition on negotiated hospital prices. Insurer competition can lead to lower premiums and reduced industry surplus, thereby depressing hospital prices; however, hospitals may also leverage fiercer insurer competition when bargaining in order to negotiate higher prices. We rely on a theoretical bargaining model to derive a regression equation relating negotiated prices to the degree of insurer competition, and use the presence of Kaiser Permanente in a hospital's market as a measure of insurer competition. We estimate a model of consumer demand for hospitals and use it to derive many of the other independent variables specified in the regression equation. Leveraging a unique dataset on negotiated prices between hospitals and commercial insurers in California in 2004, we find that increased insurer competition reduces hospital prices on average, but has a positive and empirically meaningful effect on the prices of attractive and high utility generating hospitals. This heterogeneous effect across hospitals—which has not been emphasized in the recent literature on hospital-insurer bargaining—provides incentives for hospital investment and consolidation, and implies that hospital market power can lead to high input prices even in markets where many insurers are present.

Keywords: health insurer competition, hospital prices, bargaining
JEL: I11, L13, L40

1 Introduction

Competition between health insurers has been a focus of policymakers in recent years. One of the main objectives of the Health Insurance Exchanges to be established under the Patient Protection and Affordable Care Act of 2010 is to facilitate insurer competition, with the goal of generating reduced premiums to employers and enrollees and increased coverage and quality of care.[1]

*We thank Patricia Foo for exceptional research assistance; Allan Collard-Wexler, Leemore Dafny, and David Dranove for suggestions; and seminar participants at Columbia, the FTC, Harvard, Johns Hopkins, Kellogg, LSE, NBER Summer Institute, Northwestern, NYU, and SMU for helpful comments. All errors are our own.

†Columbia University and NBER, kh2214@columbia.edu.
‡New York University Stern School of Business, rslee@stern.nyu.edu.

[1] In addition, exchanges will provide a forum where consumers who do not have access to large- or small-group health insurance plans through their employers can access insurance. They will also play a role in spreading risk so that the costs of high-need enrollees are shared more broadly across large groups.

Commentators and hospital executives have argued that this competition at the insurer level may reduce hospital prices because increased insurer competition would constrain premiums and industry surplus, limit insurers' ability to pass-through rate increases, and generate a downward pressure on provider prices.[2] However, this argument ignores the fact that the input market for health services is imperfectly competitive, and health providers—such as hospitals and physician groups—utilize their market power to negotiate reimbursement prices with insurers. As insurer competition increases, consumers become more likely to switch insurers if a particularly attractive hospital is dropped and insurers' bargaining outside options are reduced. This allows hospitals to "play" insurers off one another and provides them with greater leverage to negotiate higher rates. This offsetting positive price effect, which mitigates some of the benefits of insurer competition, is a variant of the countervailing power hypothesis that greater downstream concentration (i.e., less insurer competition) can lead to lower negotiated input prices from upstream firms (Galbraith (1952)).

This paper empirically investigates the magnitude and direction of the impact of insurer competition on negotiated hospital prices, focusing on the extent to which the effect varies across hospitals. We leverage a unique admissions and claims dataset provided by a public agency with more than one million insured individuals, which contains actual negotiated transaction prices paid by two of the largest commercial insurers in California to hospitals in 2004. We also observe the precise hospital networks offered by these two insurers. Though previous papers have found evidence that negotiated hospital prices can rise in response to increased insurer competition (Moriya et al. (2010), Melnick et al. (2010)), our study emphasizes the potential heterogeneous impact of such competition across different hospitals. We expect the most attractive hospitals to have the greatest ability to negotiate higher prices when insurer market power is low; other hospitals may see smaller price increases, or even price reductions, because the effect of insurer competition on premiums outweighs the offsetting effect. Both theoretically and empirically, such heterogeneity is crucial to consider and, to our knowledge, has not been examined in the previous literature.

We primarily study negotiated hospital prices and note that they directly affect consumer surplus through their impact on insurer premiums. In addition, changes in these prices and transfers from insurers to health providers may encourage further provider consolidation, benefit some hospitals more than others, and lead to potential distortions in investment incentives.

We begin by developing a theoretical model of bargaining between hospitals and insurers; this provides a framework for a regression equation relating negotiated prices to measures of insurer competition. The model indicates that the negotiated price between a hospital and an insurer is related to changes in the following when the hospital is dropped from the insurer's network: (i) the insurer's premiums, demand, and payments to other hospitals, and (ii) the hospital's costs and

[2] This is consistent with arguments such as: "...non-Kaiser [hospital] systems recognized the need to contain costs to compete with Kaiser [Permanente]—that is, the need to keep their own demands for rate increases reasonable enough that the premiums of non-Kaiser insurers can remain competitive with Kaiser." ("Sacramento," *CA Health Care Almanac*, July 2009 accessed at `http://www.chcf.org/~/media/MEDIA%20LIBRARY%20Files/PDF/A/PDF%20AlmanacRegMktBriefSacramento09.pdf`). See also arguments put forth by Sutter Health, a large hospital system based in Northern CA (`http://www.sutterhealth.org/about/healthcare_costs.html` accessed on July 29, 2013).

reimbursements from other insurers. Several of our regressors control for the outside options of each hospital and insurer, and require predicting utilization patterns if a hospital is dropped from a given insurer's network. We do this by estimating a model of consumer demand for hospitals, based on Ho (2006). The demand model allows us to predict hospitals' patient flows conditional on patient characteristics (including diagnosis and location) and insurer networks. However the primary dependent variables of interest, which relate to insurer competition, cannot be directly predicted using our hospital demand model. These comprise changes in the insurer's demand and premiums, as well as changes in the hospital's payments from other insurers, when a given hospital is dropped from an insurer's network. We proxy for these variables with measures of (i) the degree of insurer competition within a hospital's local market, and (ii) consumers' willingness-to-pay for access to that hospital in an insurer's network. These measures are the key variables in our pricing equation.

Our primary strategy to identify the impact of insurer competition on negotiated prices uses the intuition of a natural experiment, and focuses on the locations of Kaiser Permanente hospitals, most of which were established more than a decade before the time period in question. Kaiser is the largest insurer in California (and the largest managed care organization—MCO—in the US), with a HMO enrollee market share of approximately 40%. Kaiser is vertically integrated: i.e., it owns a network of providers and rarely refers patients to hospitals outside its network. Since non-Kaiser enrollees do not access Kaiser hospitals, and Kaiser enrollees do not access non-Kaiser hospitals, Kaiser affects the bargaining process between a non-Kaiser hospital and another commercial insurer only through insurer competition for enrollees. Furthermore, Kaiser's competitiveness, with respect to another insurer, depends crucially on the proximity of potential enrollees to one of the 27 Kaiser hospitals that were active in California in 2004. This varies considerably within a given market area, which would not be the case for another insurer that contracts with hundreds of hospitals.

We use the share of a given hospital's patients who live within 3 miles of a Kaiser Permanente hospital as our measure of insurer competition: this variable captures the extent to which consumers may switch insurers to Kaiser if that hospital is dropped from a network. The intuition is: if an insurer, such as Blue Shield (BS), loses a hospital from its network, BS will see a greater reduction in enrollment if that hospital's patients live closer to a Kaiser hospital than if they do not. In other words, proximity to a Kaiser hospital makes the alternative option of enrolling in Kaiser more desirable. Thus, hospitals whose patients are close to Kaiser hospitals may negotiate higher prices with BS than they would if Kaiser insurance were not a viable alternative.[3]

As our theoretical bargaining model makes clear, the degree of competition between an insurer and Kaiser may also affect negotiated prices along other dimensions. The main offsetting effect is that, when Kaiser is present, more intense premium competition may reduce insurer markups and therefore reduce the loss faced by an insurer upon losing a hospital from its network. This tends to

[3]This also motivates our focus on Kaiser. If the presence of Kaiser affects the price that a hospital negotiates with BS, this effect must be due to insurer competition for enrollees. In contrast, measures based on consumer proximity to other insurers would be less "clean" and easy to interpret because they often have their own contracts with the hospital and, therefore, affect the hospital-BS bargaining process through multiple channels.

reduce hospital prices.[4] We investigate the relative magnitudes of the competing effects by including a measure of hospital "quality" in the regression and interacting it with our insurer competition variable. We use a prediction of how consumers' willingness-to-pay (WTP) for an insurer's network changes when a particular hospital is removed from the network (Capps et al. (2003)). This "ΔWTP" variable, developed in the previous literature on hospital-insurer bargaining, is computed from the estimated hospital demand system.[5] Our Kaiser variable measures both the extent to which consumers may view Kaiser as a possible substitute for their current insurer, and Kaiser's negative effect on premiums, while ΔWTP captures the extent to which consumers wish to find a substitute when a particular hospital is dropped. An interaction term between these two variables helps disentangle the heterogeneous effects of insurer competition. For example, if consumers only choose to switch away from an insurer that drops a very attractive hospital from its network (e.g., if switching costs between insurers are substantial), the impact of Kaiser's presence on negotiated prices may be negative for most hospitals but positive for the most attractive hospitals (as measured by ΔWTP). However, our specification is flexible enough to allow for other relationships between the variables of interest.

Our analysis relies on the exogeneity of Kaiser hospital locations with respect to other variables we have not controlled for that can influence negotiated prices. We use market and insurer-level fixed effects and zipcode-level demographic controls, and also re-estimate our model using only locations of Kaiser hospitals built prior to 1995 to address the possibility that recent Kaiser hospitals located in response to unobserved demand conditions. We argue that variation in employer choice sets and the competitiveness of other commercial insurers are likely to be well captured by market controls and are unlikely to vary systematically at the same 3-mile radii used to measure Kaiser attractiveness. We also argue that our ΔWTP variable adequately controls for any potential differences in hospital quality that may be correlated with proximity to a Kaiser hospital.

We view our approach as a direct way to demonstrate that insurer competition is important, without requiring the assumptions or data needed to estimate a model of insurer demand and premium-setting. We wish to provide evidence that plausibly exogenous differences in insurer competitiveness across hospitals have an economically significant effect on negotiated prices. If insurer competition did not matter (for example if consumers were captive to an insurer and did not switch in response to hospital network changes, or if firms did not internalize this possibility), then we would not expect to find any impact of our Kaiser competitiveness variable on prices.[6]

[4]Increased insurer competition may limit each insurer's ability to pass-through negotiated hospital prices via higher premiums. Also the attractiveness of Kaiser as an option affects not only the outside option of an insurer, but also that of the hospital. For example, if a hospital is dropped from BS, some consumers may switch from BS to another insurer that still contracts with the hospital; however, if consumers switch to Kaiser, they cannot access that hospital. This channel may depress negotiated prices. Finally, if a hospital negotiates with several commercial insurers, the impact of Kaiser's presence on each of these individual bilateral bargains will have reinforcing effects across all bargains.

[5]The previous hospital bargaining literature uses ΔWTP as a proxy for the change in insurer premiums when a hospital is dropped from the network. When consumers are not captive and can switch insurance plans, it can also proxy for the change in insurer demand on the extensive margin.

[6]We could estimate a significant effect of the ΔWTP variable, even if consumers were captive to an insurer, for example if insurers acted as perfect agents for their enrollees and therefore adjusted their premiums in response to a

Our results support the hypothesis that insurer competition is an important determinant of hospital prices and has an heterogeneous effect across hospitals. The average effect of Kaiser's presence on a hospital's negotiated prices is negative for most hospitals. However, for the most attractive hospitals, the effect is positive: e.g., in the top quartile and decile of our ΔWTP measure, increasing the proportion of patients with local access to a Kaiser hospital by just 10% results in an increase in the negotiated price per admission of approximately \$31 and \$120 respectively; this effect increases to \$300, or 5% of the average hospital price per admission in our data, for hospitals above the 95th percentile of ΔWTP. By showing that the effect of insurer competition on negotiated prices can be substantial, we conclude that a complete analysis of the impact of health insurer competition should take into account the significant potential impact on hospital prices.

1.1 Related Literature

This paper is related to the previous literature considering the relationship between insurer competition and provider prices. One of the most recent of these papers, Moriya et al. (2010), uses a reduced-form structure-conduct-performance approach with Medstat data to analyze the impact of both insurer and hospital market power on negotiated prices. The authors regress prices on hospital and insurer concentration (measured by Herfindahl indices), use the panel structure of their data to difference out market and firm fixed effects, and find that within-market increases in insurer concentration over time are significantly associated with decreases in hospital prices. A hypothetical merger between two of five equally sized insurers is estimated to decrease hospital prices by 6.7%. However they note that their estimating equation is not derived from any formal model of the bargaining process, but rather "is best thought of as an empirical exploration of the idea" that concentration among buyers and sellers should be reflected in prices. Melnick et al. (2010) conduct a very similar analysis using estimated prices from hospital revenue data, and find that hospital prices in the most concentrated health plan markets considered are approximately 12 percent lower than in more competitive health plan markets.

Another related section of the literature focuses on how hospital prices are determined through insurer-hospital bargaining. Early papers including Town and Vistnes (2001) and Capps et al. (2003) estimate the determinants of negotiated hospital prices using specifications that are consistent with an underlying bargaining model; however, they do not specify the particular bargaining model employed, nor the effect of insurer competition on the bargaining outcome.[7] Gowrisankaran et al. (2013) and Lewis and Pflum (2013) both estimate fully-specified bargaining models; the former paper considers the impact of hospital mergers on negotiated prices, while the latter focuses on the consequences of bargaining for hospital systems' prices. Dranove et al. (2008) develops a dynamic model of the bargaining process. Though these papers consider important aspects of insurer-hospital bargaining, they rule out insurer competition (e.g., by assuming consumers can-

network change.

[7]Sorensen (2003) provides reduced form evidence that insurers with a better ability to channel patients to certain hospitals negotiate lower prices.

not switch plans in response to an insurer network change or bargaining disagreement). This is primarily in response to data limitations and modeling complexities. In contrast, Ho (2006, 2009) relaxes this assumption and estimates a model of consumer demand for hospitals and insurers given the network of hospitals offered, as an input to a model of hospital network formation (assuming a take-it-or-leave-it offers model to determine hospital prices). Lee and Fong (2012) contains a dynamic bargaining model that allows consumers to switch insurers. However, these three papers do not estimate the magnitude of the effect of insurer competition on input prices.

Our contribution is to bring the finding of the first set of papers—that insurer competition has a demonstrable effect on provider prices—into the formal bargaining framework developed and employed in the second set. By explicitly controlling for multiple complex bargaining effects and formally decomposing the offsetting effects of increased insurer competition, we are able to show theoretically and empirically that insurer competition for patients *and* hospitals has an economically-relevant and heterogeneous impact on negotiated prices.

Our research is also related to recent work finding that insurer market power can affect premiums. Dafny et al. (2012) find that greater concentration resulting from a merger of insurers is associated with a modest increase in premiums. This suggests that if insurers are able to negotiate lower prices after a merger, they are not passing cost savings on to their enrollees;[8] Dafny (2010) finds evidence consistent with this. Our finding that the input price effect of insurer competition is heterogeneous across hospitals provides another angle to interpret these premium increases: as we find that only very attractive hospitals' prices increase substantially with insurer competition, if the insurance market becomes less competitive and more concentrated, the resulting reduction in these hospital payments may not be large enough (or even present) to outweigh the impact of reduced insurer competition on premiums.

Finally, our analysis contributes to the large literature on countervailing power and bargaining in bilateral oligopoly, and the impact of changes in concentration via merger or entry on negotiated prices (e.g., Horn and Wolinsky (1988), Stole and Zweibel (1996), Chipty and Snyder (1999), Inderst and Wey (2003)).[9]

2 Theoretical Model

In this section we develop a simple bargaining model that predicts how hospital prices are determined via bilateral negotiations between insurers (also known as managed care organizations, or MCOs) and hospitals. The model highlights how increased insurer competition can affect negotiated prices, and why the net impact is ambiguous. Insights from the model will inform our empirical approach and provide the basis of our estimating equation.

[8] Dafny et al. (2012) also find evidence that increases in insurer concentration due to a large national merger reduced annual wages and employment for physicians.

[9] In a related industry, recent empirical work by Ellison and Snyder (2010) finds that larger drugstores secure lower prices from competing suppliers of antibiotics.

2.1 A Simple Bargaining Model

Consider a given market that contains a set of hospitals $\mathcal{H}$ and insurers $\mathcal{M}$. Let the current "network" of hospitals and MCOs be $\mathcal{G} \subseteq \{0,1\}^{|\mathcal{H}|\times|\mathcal{M}|}$: i.e., a consumer who is enrolled in MCO $j \in \mathcal{M}$ can only visit hospitals in j's network, which we denote $\mathcal{G}_j$. Equivalently, let $\mathcal{G}_i$ denote the set of insurers that have contracted with hospital i. Let $p_{ij} \in \boldsymbol{p}$ denote the price paid to hospital i by MCO j for caring for one of j's patients.

In any period, for a given network $\mathcal{G}$ we assume the following timing:

1. All insurers and hospitals $ij \in \mathcal{G}$ engage in simultaneous, bilateral bargaining to determine hospital prices $\boldsymbol{p}$, where each firm only knows the set of prices it has negotiated;

2. Given the network and negotiated prices $\boldsymbol{p}$, MCOs set premiums $\boldsymbol{\phi} \equiv \{\phi_j\}_{\forall j}$ to downstream consumers to maximize their expected profits;

3. Given hospital networks and premiums, consumers then choose an insurance plan;

4. Patients become sick wih diagnosis $l \in \mathcal{L}$ with some probability γ_l; those that are sick visit some hospital in their network. (In our empirical application, we will allow for heterogeneous consumers who become sick with different diagnoses with different probabilities; consumers will have different preferences for hospitals depending on their diagnosis and type.)

We define profits for MCO j to be:

$$\pi_{j,\mathcal{M}}(\boldsymbol{p},\mathcal{G}) = D_j(\boldsymbol{\phi}(\boldsymbol{p},\mathcal{G}),\mathcal{G})\left[\phi_j(\boldsymbol{p},\mathcal{G}) - \sum_{h\in\mathcal{G}_j}\sigma_{hj}(\mathcal{G})p_{hj}\right]$$

where D_j is MCO j's demand (number of enrollees), and $\sigma_{hj}(\mathcal{G})$ is the share of MCO j's enrollees who choose hospital h. We define $\sigma_{hj}(\mathcal{G}) \equiv \sum_l \gamma_l \sigma_{hj|l}$, where $\sigma_{ij|l}(\mathcal{G})$ is the share of MCO j's enrollees who choose hospital h conditional on becoming sick with diagnosis l. Similarly, we define profits for hospital i to be:

$$\pi_{i,\mathcal{H}}(\boldsymbol{p},\mathcal{G}) = \sum_{n\in\mathcal{G}_i} D_n(\boldsymbol{\phi}(\boldsymbol{p},\mathcal{G}),\mathcal{G})\sigma_{in}(\mathcal{G})(p_{in} - c_{in})$$

where c_{in} is hospital i's average cost per admission for a patient from MCO n.

Implicit in the construction of these profit functions is the assumption that consumer choices only respond to the prices that hospitals charge insurers through their response to premiums $\boldsymbol{\phi}(\cdot)$; i.e., once enrolled with an MCO, consumers are not influenced by hospital prices in choosing which hospital to visit, and the quantity and composition of consumer types who visit hospitals is not directly affected by $\boldsymbol{p}$ conditional on premiums. This assumption requires that (i) insurers are unable to steer patients to certain (e.g., lower cost) hospitals, and (ii) consumers do not respond to hospital prices when selecting where to go (e.g., zero co-insurance rates or no transparency of hospital prices to consumers). Second, we assume that hospitals are reimbursed according to an average price per admission, as opposed to a diagnosis-specific price. Consistent with this, in our empirical application we will construct an average resource-intensity-adjusted price per admission for each insurer-hospital pair.

Consider hospital $i \in \mathcal{H}$ bargaining with MCO $j \in \mathcal{M}$. We assume prices $p_{ij} \in \boldsymbol{p}$ are negotiated for all $ij \in \mathcal{G}$ via simultaneous bilateral Nash bargaining, so that each price p_{ij} maximizes each pair's Nash product:

$$p_{ij} \in \arg\max\, [\pi_{j,\mathcal{M}}(\boldsymbol{p},\mathcal{G}) - \pi_{j,\mathcal{M}}(\boldsymbol{p}_{-ij},\mathcal{G}\setminus ij)]^{\tau_M} \times [\pi_{i,\mathcal{H}}(\boldsymbol{p},\mathcal{G}) - \pi_{i,\mathcal{H}}(\boldsymbol{p}_{-ij},\mathcal{G}\setminus ij)]^{\tau_H} \;\; \forall ij \in \mathcal{G} \quad (1)$$

That is, each price p_{ij} maximizes MCO j and hospital i's bilateral Nash product, given all other prices $\boldsymbol{p}_{-ij}$, where $\pi_{j,\mathcal{M}}(\boldsymbol{p}_{-ij},\mathcal{G}\setminus ij)$ and $\pi_{i,\mathcal{H}}(\boldsymbol{p}_{-ij},\mathcal{G}\setminus ij)$ represent MCO j and hospital i's disagreement payoffs (or outside options) upon disagreement. As each bilateral bargain happens simultaneously, we assume that if hospital i comes to a disagreement with MCO j, the new network is $\mathcal{G}\setminus ij$, and all other prices are not immediately renegotiated (and, thus, remain fixed at $\boldsymbol{p}_{-ij}$).[10] This determination of prices was proposed in Horn and Wolinsky (1988), and also used in applied work, including Crawford and Yurukoglu (2012), Grennan (2013), Gowrisankaran et al. (2013), Lee and Fong (2012).[11] Finally, we assume that Nash bargaining parameters $\{\tau_M, \tau_H\}$ for MCOs and hospitals are the same across agents of the same type, and that $\tau_M + \tau_H = 1$.

To simplify our analysis, we make one more assumption: premiums do not respond to (small) changes in negotiated prices p_{ij} so that $\partial\phi_k/\partial p_{ij} \approx 0$ for all $j,k \in \mathcal{M}$, $i \in \mathcal{H}$. Since we assume prices are privately observed by each insurer-hospital pair, changes in equilibrium prices p_{ij} will not affect premiums for other insurers $-\boldsymbol{j}$. The additional assumption that small changes in one particular hospital's prices do not affect premiums is consistent with individual hospital market shares being small at the level of aggregation where premiums are set.[12] Our model does allow for the possibility that premiums can be adjusted if the network $\mathcal{G}$ changes (holding prices fixed): that is, $\boldsymbol{\phi}(\boldsymbol{p},\mathcal{G})$ may be different from $\boldsymbol{\phi}(\boldsymbol{p}_{-ij},\mathcal{G}\setminus ij)$. Furthermore, levels of premiums (both before and after disagreement) may still be influenced by the degree of insurer competition.

Under the assumptions we have made, the first-order-condition (FOC) of the maximization

[10] We show below that our main results are also robust to allowing insurers to bargain simultaneously with *hospital systems*, where each system can threaten to remove all of its hospitals upon disagreement.

[11] Collard-Wexler et al. (2013) provide a non-cooperative foundation for this bargaining solution in bilateral oligopoly.

[12] Allowing $\partial\phi_k/\partial p_{ij} \neq 0$ would allow the pass-through of negotiated prices to also be influenced by insurer competition. Though this effect is abstracted away from in this formulation, we discuss its implications later when discussing our estimates and results.

problem, given by (1), implies the following linear equation for prices:

$$p^*_{ij} = \tau_H \left[\frac{D_j\phi_j - \tilde{D}_j\tilde{\phi}_j}{D_j\sigma_{ij}} - \left(\frac{\sum_{h\in\mathcal{G}_j\setminus ij} p^*_{hj}(\sigma_{hj} - \frac{\tilde{D}_j}{D_j}\tilde{\sigma}_{hj})}{\sigma_{ij}} \right) \right] + \tau_M \left[c_{ij} - \frac{\sum_{n\in\mathcal{G}_i\setminus ij}(D_n\sigma_{in} - \tilde{D}_n\tilde{\sigma}_{in})(p^*_{in} - c_{in})}{D_j\sigma_{ij}} \right]. \tag{2}$$

where we have dropped the arguments of D_j, ϕ_j, and σ_{ij} for expositional convenience, and have used $\tilde{(\cdot)}$ to denote functions that take as arguments $\mathcal{G}\setminus ij$ (and potentially $\boldsymbol{p}_{-ij}$): for example, $\tilde{\phi}_j \equiv \phi_j(\boldsymbol{p}_{-ij}, \mathcal{G}\setminus ij)$. These represent *disagreement* outcomes for these functions, as we have assumed disagreement between hospital i and insurer j results in i's removal from j's network.[13] We rearrange (2) and multiply through by σ_{ij} (the fraction of MCO j's enrollees that visit hospital i) so that the left-hand-side (LHS) of the equation is in terms of payment from j to i per enrollee rather than per admission:

$$\underbrace{p^*_{ij}\sigma_{ij}}_{\text{hospital price / enrollee}} = \tau_H \left[\underbrace{\left(\frac{D_j\phi_j - \tilde{D}_j\tilde{\phi}_j}{D_j}\right)}_{\text{(i) } \Delta \text{ MCO revenues}} - \underbrace{\left(\sum_{h\in\mathcal{G}_j\setminus ij} p^*_{hj}(\sigma_{hj} - \tilde{\sigma}_{hj} + \frac{D_j - \tilde{D}_j}{D_j}\tilde{\sigma}_{hj}) \right)}_{\text{(ii) } \Delta \text{ MCO } j \text{ payments to other hospitals}} \right] + \tau_M \left[\underbrace{\bar{c}_i\sigma_{ij}}_{\text{(iii) hospital costs / enrollee}} - \underbrace{\sum_{n\in\mathcal{G}_i\setminus ij} \frac{(D_n\sigma_{in} - \tilde{D}_n\tilde{\sigma}_{in})}{D_j}(p^*_{in} - \bar{c}_i)}_{\text{(iv) } \Delta \text{ Hospital } i \text{ profits from other MCOs}} \right] + \epsilon_{ij} \tag{3}$$

where $\bar{c}_i$ represents hospital i's average cost of an admission, and ϵ_{ij} represents the deviation from average costs for a given MCO j. Define $\omega_{ij} \equiv c_{ij} - \bar{c}_i$, which implies ϵ_{ij} will be a function of ω_{ij} and the following demand parameters:

$$\epsilon_{ij} \equiv \tau_M \left[\omega_{ij}\sigma_{ij} + \sum_{n\in\mathcal{G}_i\setminus ij} \frac{(D_n\sigma_{in} - \tilde{D}_n\tilde{\sigma}_{in})}{D_j}\omega_{in} \right] \tag{4}$$

We assume ω_{ij} is a mean zero, independently distributed cost shock, which represents the difference between the hospital's average cost per patient and its perceived cost of treating a patient from MCO j. This difference could be due to long-term relationships with particular MCOs, for example, or to complementarities in information systems with some insurers.

[13] In Section 4.1, we also allow for hospital systems to remove all of their hospitals upon disagreement.

Discussion Equation (3) expresses the price paid from MCO j to hospital i in terms of the change in each firm's outside options due to disagreement. The first line represents changes to MCO j's gains from trade. Term (i) represents j's changes in premium revenue upon losing hospital i due to fewer patients being enrolled and lower premiums; the greater the loss, the higher is p^*_{ij}. Since this term is a function of both demand and premiums, it allows the impact of insurer competition to have both of the offsetting effects discussed earlier. On the one hand, a competitive insurance market can reduce the loss in revenues faced by an insurer upon losing a hospital, since premium markups are already low; this reduces hospital prices. On the other hand, the loss of a very attractive hospital can cause a larger change in an insurer's enrollment if there are alternative insurers present; this increases hospital prices.

Term (ii) represents the change in payments per enrollee that j makes to other hospitals in its existing network upon losing i. The first part of (ii), $\sum_{h\in\mathcal{G}_j\setminus ij} p^*_{hj}(\sigma_{hj}-\tilde{\sigma}_{hj})$, is negative, as the patients enrolled in j who used to visit i now move to other hospitals in the network. The second part of (ii), $\sum_{h\in\mathcal{G}_j\setminus ij} p^*_{hj}(\frac{D_j-\tilde{D}}{D_j}\tilde{\sigma}_{hj})$, adjusts for the fact that fewer patients are now enrolled in j. Term (ii) indicates that if j's enrollees visit higher-cost hospitals in j's network if i is dropped, then p^*_{ij} will be higher.

The second line of (3), representing changes to hospital i's gains from trade upon disagreement with MCO j, is also composed of 2 terms. Term (iii) represents hospital costs per enrollee; every unit increase in costs results in a τ_M unit increase in p^*_{ij}. Finally, (iv) represents the change in hospital i's reimbursements from other insurers $n \neq j$. The more that consumers from other MCOs visit hospital i if j drops i (which can occur if consumers switch away from j to another MCO in order to access i), then the greater is $\tilde{D}_n - D_n > 0$ and hence the higher are negotiated prices p^*_{ij}. This term also highlights the externalities across bargains: the higher hospital i's negotiated prices with MCO n, the higher will be i's prices with MCO j if j and n are substitutable.

It is worth noting that if enrollees were captive to their MCOs and they did not switch insurers upon any network change (or there were limited insurer competition), so that $D_n(\mathcal{G}\setminus ij,\cdot) = D_n(\mathcal{G},\cdot)$ for all i,j,n, then (3) would be well approximated only by:

$$p^*_{ij}\sigma_{ij} = \tau_H\left[\left(\phi_j-\tilde{\phi}_j\right)-\left(\sum_{h\in\mathcal{G}_j\setminus ij} p^*_{hj}(\sigma_{hj}-\tilde{\sigma}_{hj})\right)\right]+\tau_M\left[\bar{c}_i\sigma_{ij}\right]+\epsilon_{ij}. \tag{5}$$

Thus, finding a relationship between prices and terms on the right-hand-side (RHS) of (3), but not (5), would suggest that employers and/or their enrollees are not captive to their MCOs, and, thus, insurer competition is relevant for bargaining.

Matrix Notation For each link $a \in \mathcal{G}$, let a_H be the associated hospital and a_M be the associated MCO. We can express (3) in vector/matrix notation as:

$$\boldsymbol{p}\odot\boldsymbol{\sigma} = \tau_H[\underbrace{\boldsymbol{\phi}^{\boldsymbol{\Delta}}}_{(i)}-\underbrace{\boldsymbol{\Sigma}^{\boldsymbol{\Delta}}\boldsymbol{p}}_{(iia)}-\underbrace{\boldsymbol{D}^{\boldsymbol{\Delta}}\odot(\boldsymbol{\Sigma}\boldsymbol{p})}_{(iib)}]+\tau_M[\underbrace{\boldsymbol{c}\odot\boldsymbol{\sigma}}_{(iii)}-\underbrace{\boldsymbol{\Sigma}^{\boldsymbol{D}}(\boldsymbol{p}-\boldsymbol{c})}_{(iv)}]+\boldsymbol{\epsilon} \tag{6}$$

where $\odot$ is the Hadamard (element-by-element) product; $\boldsymbol{p}, \boldsymbol{\sigma}, \boldsymbol{c}, \boldsymbol{\epsilon}$ are $N \times 1$ vectors over all links $a \in \mathcal{G}$, where $N = |\mathcal{G}|$ (the number of contracts between all insurers and hospitals); $\boldsymbol{\phi^\Delta}$ and $\boldsymbol{D^\Delta}$ are $N \times 1$ vectors with:

$$\begin{aligned} \phi_a^\Delta &= \frac{D_{a_M}(\mathcal{G}, \cdot)\phi_{a_M}(\mathcal{G}, \cdot) - D_{a_M}(\mathcal{G} \setminus a)\phi_{a_M}(\mathcal{G} \setminus a, \cdot)}{D_{a_M}(\mathcal{G}, \cdot)} , \\ D_a^\Delta &= \frac{D_{a_M}(\mathcal{G}, \cdot) - D_{a_M}(\mathcal{G} \setminus a)}{D_{a_M}(\mathcal{G}, \cdot)} ; \end{aligned}$$

and $\boldsymbol{\Sigma}, \boldsymbol{\Sigma^\Delta}$, and $\boldsymbol{\Sigma^D}$ are $N \times N$ matrices with:

$$\begin{aligned} \Sigma_{a,b} &= \sigma_{b_H, a_M}(\mathcal{G} \setminus a) && \text{if } a_M = b_M\text{; 0 otherwise} \\ \Sigma_{a,b}^\Delta &= (\sigma_{b_H, a_M}(\mathcal{G}) - \sigma_{b_H, a_M}(\mathcal{G} \setminus a)) && \text{if } a_M = b_M,\ a_H \neq b_H\text{; 0 otherwise} \\ \Sigma_{a,b}^D &= \frac{D_{b_M}(\mathcal{G}, \cdot)\sigma_{a_H, b_M}(\mathcal{G}) - D_{b_M}(\mathcal{G} \setminus a, \cdot)\sigma_{a_H, b_M}(\mathcal{G} \setminus a)}{D_{a_M}(\mathcal{G}, \cdot)} && \text{if } a_M \neq b_M\text{; 0 otherwise.} \end{aligned}$$

The elements of (6), labelled $(i) - (iv)$, correspond to the elements of (3), where (ii) has been decomposed into two different parts, (iia) and (iib). Equation (6) will inform our estimation approach in the next section. Since negotiated prices enter both sides of (6), we will estimate this system of equations using instruments.

3 Empirical Application

We use the price equation in (6) to generate a regression equation, with the primary goal of identifying the impact of insurer competition on negotiated hospital prices. Some of the inputs to the equation (i.e., prices and hospital costs) are observed in our data. We estimate a model of hospital demand and use it, together with data on hospital and insurer characteristics, to predict as many of the other inputs as possible (i.e., the LHS and terms (iia) and (iii) of the equation). However the remaining terms—i.e., those that relate to the change in insurer demand, and insurer premiums, when a hospital is dropped—cannot be predicted so easily. These are the key terms for our analysis, since they capture the impact of insurer competition. Controlling for them explicitly would involve estimating a model of insurer demand and premium-setting, and then using estimates to predict counterfactual market shares and premiums. We choose not to adopt this approach because we do not have access to all the data needed to credibly estimate insurer demand. For example, we cannot credibly estimate preferences over many large insurers, such as Health Net and Pacificare, as they are not observed in our data. Similarly, only limited data on premiums are available, and there is significant (unobserved) variation across employers in whether they are self-insured and the level of employee contributions.

Instead we use our measure of the competitiveness of Kaiser Permanente in the hospital's market as the primary variable that captures changes in insurer demand when a hospital is dropped. Specifically, we use the share of each hospital's patients who live within 3 miles of a Kaiser Permanente hospital. The second measure is the change in consumer willingness to pay for MCO j's network if hospital i is removed. This term, ΔWTP_{ij}, was introduced in Capps et al. (2003), and accounts for both the "quality" of a hospital relative to others in the market and the existence of a viable substitute in the network. The idea behind including these variables in the price equation is that, the closer patients are to a Kaiser hospital, the more likely they are to switch insurers if a hospital is dropped from MCO j's network. Also the more attractive the hospital, the more likely they are to switch insurers if it is dropped. Both these terms, as well as their interaction, should therefore affect how an insurer's demand D_j and premium ϕ_j would change, subsequent to a disagreement with a hospital. The coefficients on the Kaiser terms are the key parameters of interest. The interaction of our Kaiser variable with ΔWTP_{ij} will help us disentangle the differential price effects of insurer competition, since hospitals that are more attractive to consumers may have a greater ability to leverage the resulting reduction in the insurer's outside option.

In this section we first discuss the data, from which negotiated prices, average hospital costs, and insurer-hospital networks can be inferred. We then briefly describe the model of consumer demand for hospitals, from which we predict the share of consumers who visit any hospital h from MCO j after a change in the observed network (i.e., $\{\sigma_{hj}(\mathcal{G} \setminus ij)\}_{\forall i,h \in \mathcal{G}_{j,\mathcal{M}}; j \in \mathcal{M}}$), and the ΔWTP_{ij} variable. Finally, we describe the variables relating to Kaiser in more detail and, in Section 3.5, present the estimating equation based on (6) and our constructed variables.

3.1 Data

Our main dataset comprises 2004 claims information for enrollees covered by the California Public Employees' Retirement System (CalPERS), an agency that manages pension and health benefits for more than one million California public employees, retirees, and their families. The claims are aggregated into hospital admissions and assigned a Medicare diagnosis-related group (DRG) code. In 2004, CalPERS offered access to a Blue Shield HMO (BS), a Blue Cross PPO (BC), and a Kaiser HMO plan. For enrollees in BS and BC, we observe hospital choice, diagnosis, and total prices paid by each insurer to a given medical provider for the admission. We have 35,289 admissions in 2004 for enrollees in BS and BC; we do not observe prices or claims information for Kaiser enrollees. We use this admissions-level data to estimate a model of consumer demand (described in the next section), conditional on the set of hospitals in the BS and BC networks (obtained directly from these insurers for 2004). We divide each price by the admission's 2004 DRG Medicare weight to account for differences in relative values across diagnoses and find the average adjusted price for each insurer-hospital pair.[14] We address price measurement error concerns by including only hospital-insurer price observations for which we observe 10 or more admissions in 2004; we also winsorize the data at the 5% level to control for outliers before constructing average prices.

[14]Hospital contracts with commercial insurers are typically negotiated as some combination of per-diem and case rates, and payments are not necessarily made at the DRG level. At the same time, Medicare DRG weights serve as an approximate means of controlling for variation in casemix and resource utilization across hospitals in constructing comparable average prices. See also the discussion in Gowrisankaran et al. (2013).

We use hospital characteristics, including location and costs, for hospitals from the American Hospital Association (AHA) survey.[15] We use demographic information from the 2000 Census.

We base our market definition on the California Office of Statewide Health Planning and Development (OSHPD) health service area (HSA) definitions. There are 14 HSAs in California. We exclude from our analysis hospitals in the BS and BC networks that are located in the 3 HSAs containing San Francisco, Oakland, and Los Angeles. These regions have high concentrations of Kaiser Hospitals but are also much more urban than other regions in our data and probably different from other areas in unobserved ways, and we are concerned that hospital pricing in these areas may be subject to unobservables that are difficult to control for.[16] Our final sample contains 233 hospital-insurer price observations (136 from BC, 97 from BS), comprising 149 unique hospitals.

3.2 Consumer Demand for Hospitals

Our model of consumer demand for hospitals closely follows Ho (2006). That paper estimates demand for hospitals using a discrete choice model that allows for observed differences across consumers. With some probability, consumer k (with type defined by age, gender, and zip code of residence) becomes ill. His utility from visiting hospital i, given diagnosis l, is given by:

$$u_{k,i,l} = \delta_i + z_i \upsilon_{k,l} \beta + \varepsilon^D_{k,i,l}$$

where δ_i are captured by hospital fixed effects, z_i are observed hospital characteristics, $\upsilon_{k,l}$ are observed characteristics of the consumer such as diagnosis and location, and $\varepsilon^D_{k,i,l}$ is an idiosyncratic error term assumed to be iid Type 1 extreme value. Hospital characteristics include location, the number of beds, the number of nurses per bed, and an indicator for for-profit hospitals. The terms $z_i \upsilon_{k,l}$ include the distance between the hospital and the patient's home zip code, and interactions between patient characteristics (seven diagnosis categories, income, and a PPO dummy variable) and hospital characteristics (teaching status, a FP indicator, the number of nurses per bed, and variables summarizing the cardiac, cancer, imaging and birth services provided by the hospital). There is no outside option, since our data includes only patients who are sick enough to go to a hospital for a particular diagnosis.[17] We estimate this model using standard maximum likelihood techniques and our micro (encounter-level) data from CalPERS. We observe the network of each insurer and, therefore, can accurately specify the choice set of each patient. We assume that the enrollee can choose any hospital in his HSA that is included in his insurer's network.

The model predicts that consumer k, who lives in market m, is enrolled in MCO j, and has

[15] Our measure of costs is average payroll per admission; using total expenses per admission and weighting by the average DRG weight per admission by hospital did not significantly change our results (or estimates for any non-cost terms).

[16] We show below that our findings are robust to the inclusion of all markets as well.

[17] The WTP variable incorporates the probability of admission to hospital for each diagnosis, conditional on age and gender, separately from the hospital demand estimates.

diagnosis l, visits hospital i with probability:

$$\sigma_{kijm|l}(\mathcal{G}) = \frac{\exp(\delta_i + z_i \upsilon_{k,l}\beta)}{\sum_{f \in \mathcal{G}_{jm}} \exp(\delta_f + z_f \upsilon_{k,l})}$$

(where $z_i \upsilon_{k,l}$ again includes individual, diagnosis, and hospital interactions, including distance). Consequently, by taking a weighted average over the commercially insured population of the market, we obtain the share of MCO j's enrollees who visit hospital i in market m:

$$\sigma_{ijm}(\mathcal{G}) = \sum_{k \in m} \frac{N_{km}}{N_m} \gamma_k^a \sum_{l \in \mathcal{L}} \gamma_{kl} \sigma_{kijm|l}(\mathcal{G})$$

where $N_{k,m}$ is the commercially-insured population of market m in age-gender-zip code group k, γ_k^a is the probability that consumer k is admitted to any hospital (conditional on age and gender) and $\gamma_{k,l}$ is the probability of diagnosis l, conditional on admission, age, and gender. We compute the probabilities $\{\gamma_k^a\}_{\forall k}$ by comparing the total number of admissions from commercial insurers in California, by age and gender, from OSHPD discharge data 2003 to Census data on the total population commercially insured.[18] Probabilities $\{\gamma_{k,l}\}_{\forall k,l}$ are the realized probabilities for commercially insured patients in California, taken from OSHPD discharge data for 2003.

Further details on the demand model, together with estimates, are given in Appendix A.

3.3 Willingness-to-Pay

We follow previous papers, such as Capps et al. (2003) and Farrell et al. (2011), by using a measure of consumer willingness-to-pay (WTP) for a hospital in a particular network as a proxy for the change in consumer surplus when the hospital is dropped from a network. We use the estimated demand model to predict the ΔWTP variable for our application, which is the change in consumer WTP when a hospital is added to the network observed for Blue Shield or Blue Cross in 2004. Given the assumption on the distribution of $\epsilon^D_{k,i,l}$, individual k's expected utility from the hospital network offered by plan j when he has diagnosis l can be expressed as:

$$EU_{k,j,l}(\mathcal{G}_{j,m}) = \log\left(\sum_{h \in \mathcal{G}_{j,m}} \exp(\hat{\delta}_h + z_h \upsilon_{k,l}\hat{\beta})\right)$$

where $\mathcal{G}_{j,m}$ is the set of hospitals offered to enrollees in plan j in market m. The change in expected utility from having hospital $i \in \mathcal{G}_{j,m}$ (for a given diagnosis l) in the network is then given by:

$$\Delta EU_{k,i,j,l} = EU_{k,j,l}(\mathcal{G}_{j,m}) - EU_{k,j,l}(\mathcal{G}_{j,m} \setminus ij)$$

[18] An alternative method, using CalPERS data for both numerator and denominator, generated similar results.

Prior to enrolling in insurer j's plan (and, thus, prior to knowing whether or not he will be sick), individual k's expected benefit from having i in network is given by:

$$\Delta WTP_{k,i,j} = \gamma_k^a \sum_l \gamma_{k,l} \Delta EU_{k,i,j,l}$$

Following the same approach as the construction of $\sigma_{ijm}(\mathcal{G})$, we take a weighted average over the commercially insured population of the market to generate the following measure we use in our analysis:

$$\Delta WTP_{i,j,m} = \sum_{k \in m} \frac{N_{k,m}}{N_m} \Delta WTP_{k,i,j}$$

It is worth stressing that although we refer to $\Delta WTP_{i,j,m}$ as the change in consumers' willingness-to-*pay* for insurer j's network upon losing hospital i, it is measured in utils, not dollars, in this specification. Nonetheless, the relative differences across hospitals' $\Delta WTP_{i,j,m}$ values is informative. In particular, this value measures both hospital *quality* and *substitutability*. For example, a hospital with a larger value of δ_i will tend to have a higher value of $\Delta WTP_{i,j,m}$. However, this is mitigated if insurer j has a hospital i' with similar fixed effect $\delta_{i'}$ and characteristics $z_{i'}$, since i and i' are then closer substitutes for one another.[19]

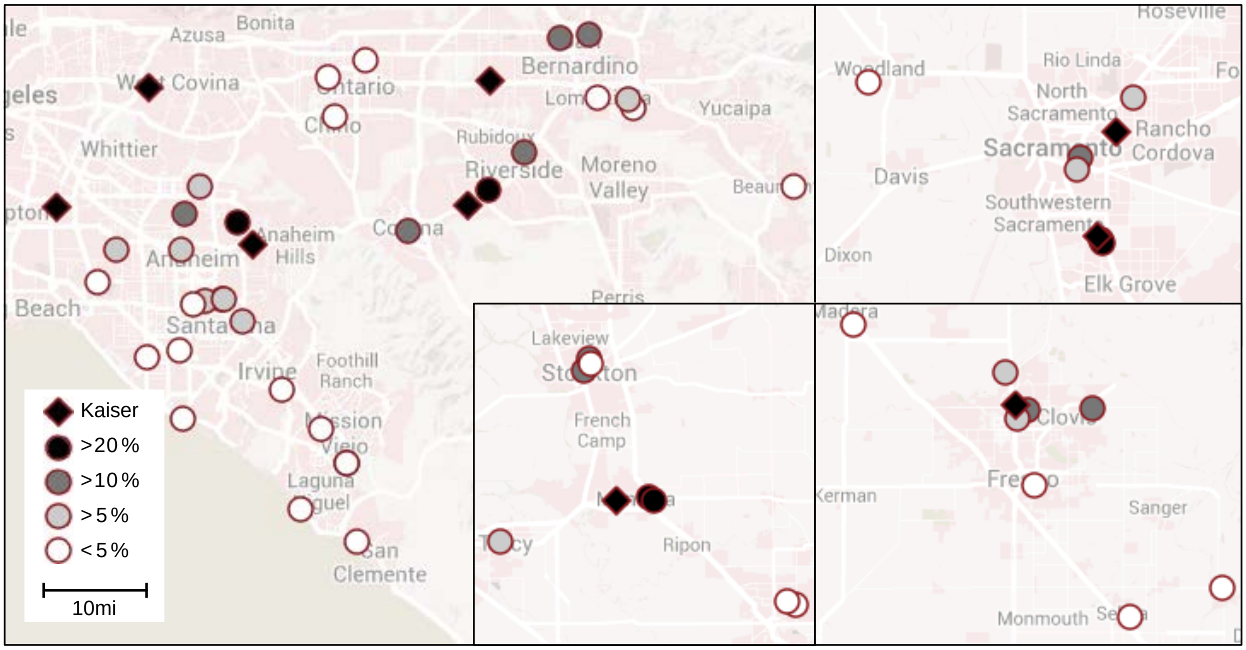
We note that the estimated demand model is valuable for this application for three reasons. First, as in Capps et al. (2003), Ho (2006), and other papers, it generates a micro-founded measure of the attractiveness of each hospital to insurer j. Second, because we observe enrollees' choice sets, we are able to obtain estimates for the actual population of interest (Blue Shield and Blue Cross HMO and PPO enrollees), rather than estimating demand for a different population (e.g., indemnity enrollees, who have unconstrained choice sets) and assuming that preferences are fixed across populations, conditional on observables, as in many previous papers. Finally, allowing expected utility to vary explicitly by age and gender, through the $z_i \upsilon_{k,l}$ terms, enables us to account for changes in selection of particular types of patients across other hospitals, when hospital i is dropped. For example, the predicted change in insurer payments to other hospitals (term (iia) in the main regression equation) accounts for predicted changes in the proportions of different enrollee types visiting each hospital and their probabilities of admission, after this network change.

3.4 Measure of Insurer Competition: Kaiser Permanente

Our measure of insurer competition is intended to capture the extent to which insurer j's demand, D_j, is affected by losing a given hospital i from its network. We use the proximity of consumers to a hospital owned by Kaiser Permanente. Kaiser is a vertically integrated MCO based in California. It was originally established to provide insurance for construction, shipyard, and steel mill workers for the Kaiser industrial companies in the 1930s, and was opened to the public in 1945. It has been

[19] We weight by the commerically insured population (from the Census data), as opposed to the population onboard each insurer (which can be estimated from our data), for two main reasons: (i) some age-sex-zip code bins are not well populated in our data, and (ii) weighting by the market population will ensure our average ΔWTP measure is invariant to the potential selection of observable consumer types onto insurance plans.

Figure 1: Exposure to Kaiser Hospitals



Notes: Kaiser (diamonds) and non-Kaiser (circles) hospitals near (clockwise from top-left): Orange County, Sacramento, Fresno, and Stockton. Non-Kaiser hospitals in LA county are not displayed. Percentages indicate the share of hospital discharges of patients from zip codes within 3 miles of a Kaiser hospital.

extremely successful and is now the largest MCO in the US; it had 37% of the HMO market in California in 2004.

The idea behind our identification strategy is that, the closer hospital i's patients are to a Kaiser hospital, the more likely they are to switch to Kaiser insurance on losing access to hospital i. This requires Kaiser to be a viable substitute for other commercial MCOs in the relevant markets. The assumption seems reasonable based on enrollment data from CalPERS: there is little evidence that Kaiser enrollees are observably different from consumers who select into other MCOs. The average salary of CalPERS employees who were enrolled in Kaiser in 2004 was $48,305 (standard deviation $19,390) compared to an average of $50,357 (standard deviation $19,918) for Blue Shield and $55,707 (standard deviation $23,706) for the largest Blue Cross plan.[20] The average family size for all three plans was between 2.12 and 2.40 (with Kaiser in the middle at 2.19), and the mean age of the primary employee was 51.5 in Kaiser, compared to 47.6 in BS and 51.4 in BC choice. The summary statistics in Section 4 demonstrate that Kaiser hospitals are also similar to non-Kaiser hospitals on most observable dimensions. Historically Kaiser may not have been considered a viable substitute for other commercial insurers by some consumers, but many details of its service offerings and its enrollee characteristics are now very similar to those of other plans.

Our Kaiser variable measures the share of hospital i's patients who come from zip codes that are

[20] Salary data were provided by CalPERS in 16 salary bands. These numbers are imputed average salaries in each insurer.

within 3 miles of a Kaiser Permanente hospital (though our results are robust for other distances and using travel times instead of distance-based measures). Specifically, we use the OSHPD 2003 data to define the catchment area of each hospital as the set of zip codes from which its commercially insured patients travel. We then construct a weighted average across the catchment area using the number of commercial admissions from that zip code in the OSHPD data. This variable takes advantage of the fact that Kaiser's convenience to patients differs substantially across geographic areas, since it is a vertically integrated insurer with only 27 hospitals in California in 2004, and it rarely offered access to hospitals outside its own organization. We hypothesize that consumers living in zip codes within easy reach of a Kaiser hospital will be much more willing to switch to Kaiser than other consumers. Our empirical approach is based on this hypothesis, and it also assumes that consumer willingness to switch to other insurers (which are not explicitly controlled for in our regression) varies less discretely across zip codes and can be accounted for using HSA fixed effects.

Eleven out of 149 unique hospitals in our sample have greater than 20% of their discharged patients from zip codes within 3 miles of a Kaiser hospital; 15 have between 10-20% share; and 17 are between 5-10%. Figure 1 displays this variation in 4 different geographic areas of California (Orange County, Sacramento, Fresno, and Stockton) by plotting locations of Kaiser and non-Kaiser hospitals, with different levels of "exposure" to Kaiser being designated by different shaded circles. Note that although physical proximity of a non-Kaiser hospital to a Kaiser hospital is correlated with our Kaiser variable (and indeed, our analysis is robust to this alternative definition of exposure to Kaiser), our variable captures more than just physical distance. For example, in Fresno, although there are two hospitals near the center of the city (designated by two light grey circles) that are closer in distance to the Kaiser hospital (designated by a black diamond) than another hospital to their east (designated by a dark grey circle), this further hospital to the east has a greater share of patients who live close by the Kaiser hospital.

3.5 Regression Equations

Equations (3)-(6), from the bargaining model developed in the previous section, motivate our main regression equation:

$$\begin{aligned}
\underbrace{P_{ij}}_{\hat{p}_{ij}\hat{\sigma}_{ij}} &= \alpha_1 \underbrace{\text{Cost}_{ij}}_{\bar{c}_i\hat{\sigma}_{ij}} + \alpha_2 \underbrace{\Delta Pmt_{j,\setminus ij}}_{\sum_{h\in\mathcal{G}_j\setminus ij}\hat{p}_{hj}(\hat{\sigma_{hj}}-\hat{\tilde{\sigma}}_{hj})} \\
&\quad +\alpha_3 \Delta WTP_{ij} + \alpha_4 Kaiser_i + \alpha_5 Kaiser_i \times \Delta WTP_{ij} \\
&\quad + \underbrace{Pmt_{j,\setminus ij}}_{\sum_{h\in\mathcal{G}_j\setminus ij}\hat{p}_{hj}(\hat{\tilde{\sigma}}_{hj})} [\alpha_6 + \alpha_7 Kaiser_i + \alpha_8 Kaiser_i \times \Delta WTP_{ij}] \\
&\quad + \boldsymbol{HSA}_m + BS_j + \boldsymbol{\beta} \times \boldsymbol{demogs}_i + \varepsilon_{ij}.
\end{aligned} \tag{7}$$

Here $P_{ij} \equiv \hat{p}_{ij}\hat{\sigma}_{ij}$ is the dependent variable in (6) and corresponds to the observed payment made to hospital i by MCO j per enrollee.[21,22]

Two of the right-hand-side variables in equation (6) are included explicitly in the regression: these are hospital i's average cost per enrollee of MCO j ($\text{Cost}_{ij} \equiv \bar{c}_i\hat{\sigma}_{ij}$), and the change in MCO j's payments per enrollee to other hospitals when hospital i is dropped from j's network ($\Delta Pmt_{j,\setminus ij}$). The cost term, like the prices, is weighted by $\hat{\sigma}_{ij}$ so that it represents the hospital's predicted cost per MCO enrollee (generated using i's share of j's enrollees taken from the demand model) rather than per admission. $\Delta Pmt_{j,\setminus ij}$ uses the demand system to infer other-hospital market shares when i is dropped from j's network, and combines these estimates with prices from the CalPERS data. It is worth noting that $\{\alpha_1, \alpha_2\}$ correspond to $\{\tau_M, -\tau_H\}$, the insurer and hospital bargaining parameters, in (6). We later test and cannot reject the restriction $\alpha_1 - \alpha_2 = 1$, thereby providing a check on our model specification.

The second and third lines in (7) contain variables that serve as proxies for the terms in (6) involving changes in insurer demand ($D_j(\mathcal{G}, \cdot) - D_j(\mathcal{G} \setminus ij, \cdot)$) and premiums ($\phi_j(\mathcal{G}) - \phi_j(\mathcal{G} \setminus ij)$) upon disagreement: that is, terms (i), (iib), and (iv). The terms in the second line proxy for the change in MCO j's revenues, and the change in payments to hospital i from other insurers, when j drops i. In order, they are ΔWTP_{ij}; our measure of Kaiser competitiveness $Kaiser_i$; and an interaction term.[23,24] The third line controls for the change in MCO j's payments to other hospitals, and takes advantage of the fact that one element of this change ($Pmt_{j,\setminus ij}$) can be predicted directly from the hospital demand estimates. We also include HSA fixed effects $\boldsymbol{HSA}_m$, an indicator that distinguishes between insurers BS_j, and demographic controls for the hospital's zip code, $\boldsymbol{demogs}_i$.[25] We discuss the role of these control variables in the following section.

3.6 Estimation and Identification

The econometric error in (7) $\varepsilon_{ij} \equiv \epsilon_{ij} + \nu_{ij}$ includes two sources of error. The first, ϵ_{ij}, is the MCO-hospital-specific cost shock defined in (4). The second, ν_{ij}, represents the error introduced by using proxies for terms (i), (iib), and (iv) in our estimating equation. It will contain any elements

[21] As in the construction of our ΔWTP measure, we construct $\hat{\sigma}_{ij}$ using weighted averages over age groups and diagnoses.

[22] We omit the interaction term $Pmt_{j,\setminus ij} \times \Delta WTP_{ij}$ in our main specification. Including it does not yield a significant coefficient and does not significantly change any other estimate in both OLS and IV specifications. Furthermore, there is a weak instrument concern when this variable is included.

[23] We drop the market subscript m in ΔWTP_{ij} with the understanding that this term remains market-specific.

[24] Much of the previous literature on hospital-insurer bargaining has used ΔWTP_{ij} to proxy for a MCO's premium change when a hospital is removed from the network, absent insurer competition effects (Capps et al. (2003) and Gowrisankaran et al. (2013)). Note that this requires a somewhat different insurer objective function than that assumed in our paper. For example insurers could be assumed to be perfect agents for their enrollees; in that case removing a hospital from the network will lead to a premium reduction, even if enrollees cannot change plans in response. However, as already noted, this variable is likely also to help capture the extent to which an insurer's demand is influenced by the network change.

[25] We have data for only 2 insurers, so our insurer fixed effects comprise an indicator for BS only. Demographic controls include population per square mile in the hospital's county and the following variables (measured both in the hospital's zip code and also as a weighted average across zips in its catchment area): median income, percent white, percent black, percent Hispanic, and percent of the population aged 55-64.

of these which are not controlled for by the observables on the last three lines of equation (7). In essence, ν_{ij} captures unobserved differences in how consumers substitute across insurers, and other variation in demand and/or costs, that we have not explicitly controlled for and that could affect prices.

Identification of Kaiser Terms

Identification relies on the plausible exogeneity of $Kaiser_i$ with respect to ν_{ij}. We take several steps to account for a number of different possible unobservables. We first consider the possibility that Kaiser could have responded to local demand shocks when choosing locations for its hospitals, and these demand shocks could also have affected prices. Table 11 in the Appendix provides information on the history of the 27 Kaiser hospitals in California that were open in 2004. Most of the hospitals were new constructions (rather than acquisitions) that were opened during or before the 1970s. Only 4 of the 27 were opened after 1990. Given this long history, and the fact that 10- or 15-year lagged hospital locations are unlikely to be correlated with 2004 demand shocks, it seems unlikely that our results are caused by endogenous location choices for Kaiser hospitals. As a robustness test, we repeat the analysis using the location of Kaiser hospitals in 1995, rather than the 2004 locations used in the main analysis; this test has little effect on our estimates.

It is also possible that the location and characteristics of non-Kaiser hospitals responded to the presence of Kaiser hospitals. We assume that the ΔWTP_{ij} variable in our regression equation adequately controls for any such effects. As it is derived from a detailed model of consumer demand for hospitals, the ΔWTP_{ij} variable captures the impact of any hospital characteristics that consumer choice responds to, as well as the extent to which a hospital is substituted for another within any particular insurer's network.

Other unobserved factors that are likely to have an impact on prices include the availability of other insurers and the size of the menu of insurance plans offered by employers in the area. As noted in Dafny et al. (2013), employers' plan menus are often small. Indeed, in their national data in 2004 only around 25% of large employers offered more than 2 plans to their employees. While employers can change their menus in response to changes in hospital networks, variation in current menus across employers will clearly affect the ability of consumers to switch plans. Thus, if either other-insurer presence, or employer plan menus, are correlated with Kaiser presence, they will affect the interpretation of our estimates. We assume that employer menus are sufficiently fixed within-market that the variation is captured by our HSA fixed effects and demographic controls. The HSA fixed effects are also assumed to control for levels of competition from other insurers. This amounts to an assumption that Kaiser's attractiveness within an HSA is much more localized than that of other insurers, because other insurers contract with hundreds of hospitals in California as opposed to just 27 for Kaiser. Furthermore it is unlikely that any within-HSA variation in other-insurer attractiveness to consumers is correlated with the 3 mile radii used to identify Kaiser attractiveness in our analysis.

Finally, we note that $Kaiser_i$ will be correlated with prices p^*_{in} negotiated by hospital i, with other insurers n in (2). Consequently, we interpret the impact of $Kaiser_i$ on prices between hospital i and insurer j as the net effect across all of i's bargains.

Selection Concerns

Another potential concern is that Kaiser could select particular types of enrollees, leaving other types to be treated by nearby non-Kaiser hospitals; this may affect the interpretation of our results. We address the possibility that Kaiser could select based on enrollee sickness level by using DRG-adjusted admission prices to control for differences in resource utilization across patients. We also note that the correlation between average hospital DRG weights and our Kaiser measure is low (0.08), implying that there does not seem to be significant selection on sickness level in our sample. Furthermore, including hospital costs in the regression equation controls for the possibility that Kaiser selects enrollees with a particularly high or low preference for service, leaving nearby non-Kaiser hospitals to treat the remaining selected sample.

One additional selection story is that Kaiser selects enrollees based on price sensitivity, implying an effect on optimal non-Kaiser prices. We note above that Kaiser and non-Kaiser enrollees in our data do not differ on average on demographics such as income, age, and family size, making such a story seem fairly unlikely. In addition, such selection seems more likely to affect premiums than hospital prices, since the former are the primary prices faced by the enrollee. We acknowledge that hospital prices could be affected in cases where the insurer charges a co-insurance rate, rather than a fixed copay (i.e., some fixed proportion of the hospital price is paid by the patient). Since in our data Blue Cross uses co-insurance rates while Blue Shield uses only copays, we run our analysis using only Blue Shield prices and enrollees and find that our results are robust, thereby mitigating this concern.

Instruments for the Price Terms

We estimate (7) using generalized method of moments (GMM) under the assumption $E[\boldsymbol{\varepsilon}|\boldsymbol{Z}] = 0$, where $\boldsymbol{Z}$ is a vector of instruments. Since prices are endogenous, we include in $\boldsymbol{Z}$ only RHS variables in (7) that are not functions of prices: that is, we exclude any variable that is a function of $\Delta Pmt_{j,\setminus ij}$ or $Pmt_{j,\setminus ij}$. We also include the following instruments for the price terms:

$$\sum_{h \in \mathcal{G}_j \setminus ij} \bar{c}_h(\hat{\sigma}_{hj} - \hat{\hat{\sigma}}_{hj}), \qquad \sum_{h \in \mathcal{G}_j \setminus ij} \bar{c}_h(\hat{\hat{\sigma}}_{hj}),$$
$$\sum_{h \in \mathcal{G}_j \setminus ij} \Delta WTP_{hj}(\hat{\sigma}_{hj} - \hat{\hat{\sigma}}_{hj}), \qquad \sum_{h \in \mathcal{G}_j \setminus ij} \Delta WTP_{hj}(\hat{\hat{\sigma}}_{hj}),$$

interacted with a constant, ΔWTP_{ij}, $Kaiser_i$, and $\Delta WTP_{ij} \times Kaiser_i$.[26] These excluded instruments, which comprise functions of costs and ΔWTP_{hj} of *other hospitals* ($h \neq i$) *in an insurer's*

[26]We use two measures of costs in our instruments, comprising average payroll and average total expenditures per admission computed from the AHA survey data. Interactions with these costs and ΔWTP measures for other hospitals on a network provide 24 excluded instruments in $\boldsymbol{Z}$.

Table 1: Summary Statistics

	Mean	S.D.
P_{ij}($ per enrollee)	25.10	38.17
ΔWTP	0.11	0.21
$\Delta Pmt_{j\setminus ij}$ ($)	-25.03	34.03
$Pmt_{j\setminus ij}$ ($)	348.16	97.17
$Cost_{ij}$ ($ per enrollee)	20.77	26.79
Blue Shield	0.42	0.49
(3mi) $Kaiser_i$ (2004)	0.05	0.10
(3mi) $Kaiser_i$ (1995)	0.04	0.08
N	233	

Notes: Summary statistics on the dataset used to run price regressions. N=233 hospital-insurer pairs. All costs and prices are rescaled to $ per enrollee (accounting for probability of admission to hospital, conditional on age and gender)

network, will be correlated with an insurer's payments to other hospitals.[27]

Recall that $\varepsilon_{ij} \equiv \epsilon_{ij} + \nu_{ij}$, which are defined at the beginning of Section 3.6. As we have assumed that $\omega_{ij} \equiv c_{ij} - \bar{c}_i$ is independent and mean zero, ϵ_{ij} (defined as a function only of ω_{ij} in (4)), will be orthogonal to non-price variables on the RHS of (7) and our set of instruments. Furthermore, we argue that functions of *other* hospital costs and ΔWTPs have little additional explanatory power (after controlling for the existing regressors in (7)) for the terms (i), (iib), and (iv) comprising MCO j's change in demand and premiums upon losing a hospital i. Hence, these functions are uncorrelated with ν_{ij}, implying the validity of our instruments.

4 Estimation Results

We begin with summary statistics of our data in Table 1. The average price paid per enrollee is $25.10 (standard deviation 38.17); this corresponds to an average price per patient of $5978 (and an average probability that an enrollee is admitted to a particular hospital of 0.004). When hospital j is dropped from the network, the insurer pays other hospitals an additional $25.03, on average, and total other hospital payments increase to $348.16. We use payroll expenses per admission as our hospital cost measure: we regard this as a reasonable proxy for resource use on the particular patient. The mean expense per enrollee is $20.77 (standard deviation $26.79). Finally the mean ΔWTP_{ij} is 0.11 (standard deviation 0.21), and the mean fraction of a hospital's patients that are within 3 miles of a Kaiser hospital is .05 (standard deviation .10) in 2004.

Table 2 compares the characteristics of Kaiser hospitals to those of the hospitals included in our regressions. We exclude from this comparison both non-Kaiser and Kaiser hospitals located in San Francisco, Oakland, and Los Angeles because these HSAs are not included in our baseline regression analysis. The table indicates that there are some differences on average between the remaining 12

[27] Angrist-Pischke first-stage F-statistics for all instrumented variables are greater than 23 except for $Pmt_{j\setminus ij}$ (7.5); exclusion of this term yielded no statistically significant different estimates for any coefficient in any OLS or IV specification reported in Tables 3-4.

Table 2: Characteristics of Kaiser and Other Hospitals

	Non-Kaiser Hospitals	Kaiser Hospitals
Number of beds	168.5 (126.1)	214.3 (112.6)
Nurses per bed	1.25 (0.53)	1.81 (0.66)
Physicians per bed	0.04 (0.09)	0.52 (0.65)
Offer CT scans	0.64 (0.48)	0.64 (0.50)
Offer PET scans	0.10 (0.30)	0.18 (0.40)
Have a NICU	0.28 (0.45)	0.36 (0.50)
Offer angioplasty	0.28 (0.45)	0.09 (0.30)
Offer oncology services	0.44 (0.50)	0.55 (0.52)

Notes: Summary statistics comparing the hospitals in our price regressions to the Kaiser hospitals in our data. N=149 non-Kaiser hospitals and 12 Kaiser hospitals. Providers located in San Francisco, Oakland and Los Angeles HSAs are excluded. Characteristics taken from the American Hospital Association data 2003-4.

Kaiser hospitals and the others in our data. Kaiser hospitals are larger, with 214 beds on average, compared to 169 for other hospitals. They have more nurses per bed and more physicians per bed. Their service provision is similar to that of other hospitals in many cases: for example, 64% of both Kaiser and non-Kaiser hospitals provide CT scans. Some services are provided less frequently by Kaiser hospitals (angioplasty is one example). However the equivalent numbers for Positron Emission Tomography, one of the highest-tech imaging services listed in our data, are 18% and 10% respectively. Birthing services are also provided in substantially more Kaiser hospitals: 36% of Kaiser facilities in our data have a neonatal intensive care unit, for example, compared to 28% of other hospitals. We conclude that there is no clear evidence in our data that Kaiser should be regarded as a poor substitute for other health insurers.

Tables 3-4 contain our regression results. Standard errors are clustered by hospital.[28] Table 3 begins our build-up to the complete equation (7). It excludes the terms that contain $Kaiser_i$ and its interactions, but includes all market, insurer, and demographic controls. We begin in Model 1 of Table 3 by including ΔWTP and hospital i's predicted cost per enrollee. Our findings are consistent with the previous literature: we estimate positive and significant coefficients on both ΔWTP and cost variables. When we add $\Delta Pmt_{j,\setminus ij}$ in Model 2, it has the expected negative coefficient (but is insignificant without instrumenting); all coefficients do not significantly change from Model 1. The signs on all estimates are consistent with the predictions of our bargaining model laid out in (3).

Model 3 in Table 3 contains our first test of the importance of insurer competition. We add $Pmt_{j,\setminus ij}$, which occurs in two places in equation (3): in $\Delta Pmt_{j,\setminus ij}$, and (separately) in an interaction with $((D_j - \tilde{D}_j)/D_j)$. We infer that this term should be significant, conditional on $\Delta Pmt_{j,\setminus ij}$, only if insurers lose patients upon dropping a hospital. Our OLS results support this, since the coefficient on $Pmt_{j,\setminus ij}$ is negative and significant. However, the coefficient is small, positive, and insignificant once instruments are used.

[28] Clustering by insurer-market resulted in slightly different (due to GMM estimation) but broadly similar estimates, with the main findings still statistically significant.

Table 3: Base Price Regressions

	(1) Model 1	(2) Model 2	(3) Model 2 IV	(4) Model 3	(5) Model 3 IV
ΔWTP_{ij}	61.57***	58.06***	53.12***	52.24***	55.14***
	(10.98)	(19.22)	(7.498)	(18.48)	(8.775)
$Cost_{ij}$	0.859***	0.791***	0.534***	0.720**	0.556***
	(0.119)	(0.290)	(0.150)	(0.281)	(0.159)
$\Delta Pmt_{j\setminus ij}$		-0.0780	-0.324***	-0.168	-0.296**
		(0.328)	(0.125)	(0.321)	(0.141)
$Pmt_{j\setminus ij}$				-0.0599***	0.0117
				(0.0209)	(0.0272)
Observations	233	233	233	233	233

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results for regression equation (7). Dependent variable is expected price per enrollee paid by insurer j to hospital i. $\Delta\,\mathrm{Pr}\,ice$ is the change in expected payments to other hospitals, per enrollee, if hospital i is dropped from the network. "Hospital cost" is the cost of hospital i weighted by the average probability that an enrollee in insurer j will be admitted to hospital i. ΔWTP is the consumer willingness-to-pay for hospital i to be added to insurer j's network; see Section 2 for details. Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

Main Results and Magnitudes. Table 4 reports our main results when we add additional terms meant to proxy for insurer competition. We begin by adding $Kaiser_i$ (the share of hospital i's patients who live within 3 miles of a Kaiser hospital) and its interaction with $Pmt_{j,\setminus ij}$. We hypothesize that the offsetting effects of insurer competition may imply differential effects across hospitals. We thus add a term interacting ΔWTP_{ij} (hospital i's contribution to MCO j's network) with $Kaiser_i$, as well as a triple interaction with both $Kaiser_i$ and $Pmt_{j,\setminus ij}$. The interaction terms allow the insurer competition effect to differ across hospitals. For example, the effect of Kaiser's presence on insurers' outside options may be greater for more attractive hospitals, perhaps because consumers face switching costs such as the need to change primary physicians and therefore change insurers only if very attractive hospitals are dropped.

The columns labeled Model 4 and Model 4 IV in the table report our main results for the OLS and IV specifications respectively. Both sets of estimates are consistent with our hypothesis. The $Kaiser_i * \Delta WTP_{ij}$ coefficient is positive, while its interaction with $Pmt_{j,\setminus ij}$ is negative, and both are significant at the 1% level. The combined effect of the estimated coefficients (largely driven by the negative coefficient on $Kaiser_i$) is a negative effect of competition from Kaiser on negotiated prices for most hospitals. If we consider the hospitals above the 25th or 50th percentile of ΔWTP_{ij}, increasing the share of patients who have access to a Kaiser hospital within 3 miles of their zip code by one standard deviation (.10) reduces prices by \$400 or \$125 on average, respectively (compared to a mean price of \$5978 in our sample). However, due to the positive coefficient on $Kaiser_i{*}\Delta WTP_{ij}$,

Table 4: Price Regressions including Insurer Competition Measure

	(1) Model 4	(2) Model 4 IV
ΔWTP_{ij}	45.74**	49.84***
	(18.47)	(6.231)
$Cost_{ij}$	0.733**	0.328***
	(0.286)	(0.0980)
$\Delta Pmt_{j\setminus ij}$	-0.196	-0.463***
	(0.317)	(0.0759)
$Pmt_{j\setminus ij}$	-0.0486**	-0.00596
	(0.0201)	(0.0190)
(3mi) $Kaiser_i$	-157.8*	-299.5***
	(90.43)	(78.23)
(3mi) $Kaiser_i * Pmt_{j\setminus ij}$	0.410	0.816***
	(0.254)	(0.225)
(3mi) $Kaiser_i * \Delta WTP_{ij}$	1017.5***	1330.8***
	(215.4)	(195.5)
(3mi) $Kaiser_i * \Delta WTP_{ij} * Pmt_{j\setminus ij}$	-2.815***	-3.556***
	(0.624)	(0.537)
Observations	233	233

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Results for regression equation (7). Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

the effect becomes positive for the most attractive hospitals. The average effect for hospitals above the 75th percentile of ΔWTP_{ij} is a price increase of \$31 per admission, which increases to \$120 for hospitals above the 90th percentile of ΔWTP_{ij} and to \$299 for hospitals above the 95th percentile.

Model 4 IV also reports statistically significant coefficients on $Cost_{ij}$ and $\Delta Pmt_{j,\setminus ij}$. As discussed earlier, the coefficients on these terms correspond to the bargaining weights $\{\tau_M, -\tau_H\}$ of MCOs and hospitals from our bargaining model in (3). The sum of the absolute values of these two estimated coefficients equaling 1 cannot be statistically rejected, which is consistent with our model.

4.1 Robustness

We now discuss the results of several robustness tests.

Alternative Distances. Table 5 reports results from using our full model specification (Model 4 IV) but varying the distance by which the $Kaiser_i$ variable is defined: that is, $Kaiser_i$ is the share of hospital i's patients who live within x miles of a Kaiser hospital. The column labeled $3mi$

Table 5: Price Regressions with Alternative Distances

	(1) 2 mi	(2) 3 mi	(3) 4 mi	(4) 5 mi	(5) 7 mi	(6) 10 mi
ΔWTP_{ij}	49.23***	49.84***	42.69***	44.66***	40.17***	42.47***
	(7.497)	(6.231)	(7.140)	(6.702)	(7.660)	(8.286)
$Cost_{ij}$	0.321***	0.328***	0.282***	0.292***	0.269**	0.278***
	(0.0989)	(0.0980)	(0.101)	(0.105)	(0.106)	(0.0996)
$\Delta Pmt_{j\setminus ij}$	-0.502***	-0.463***	-0.553***	-0.535***	-0.578***	-0.586***
	(0.0789)	(0.0759)	(0.0799)	(0.0813)	(0.0812)	(0.0733)
$Pmt_{j\setminus ij}$	0.000145	-0.00596	-0.0156	-0.0150	-0.0237	-0.0321*
	(0.0175)	(0.0190)	(0.0177)	(0.0182)	(0.0188)	(0.0191)
$Kaiser_i$	-260.7*	-299.5***	-196.2***	-110.5***	-74.16***	-42.15***
	(144.1)	(78.23)	(53.93)	(32.23)	(21.84)	(12.68)
$Kaiser_i * Pmt_{j\setminus ij}$	0.702*	0.816***	0.552***	0.298***	0.207***	0.119***
	(0.404)	(0.225)	(0.157)	(0.0942)	(0.0652)	(0.0387)
$Kaiser_i * \Delta WTP_{ij}$	1477.4***	1330.8***	914.4***	481.3***	317.1***	153.0***
	(513.8)	(195.5)	(189.5)	(159.1)	(99.96)	(57.12)
$Kaiser_i * \Delta WTP_{ij} * Pmt_{j\setminus ij}$	-4.241***	-3.556***	-2.536***	-1.341***	-0.909***	-0.488***
	(1.342)	(0.537)	(0.502)	(0.392)	(0.244)	(0.139)
Observations	233	233	233	233	233	233

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: GMM results for regression equation (7), instrumenting for all price terms, where $Kaiser_i$ is the share of hospital i's patients who live within x miles of a Kaiser hospital. Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

in Table 5 corresponds to column (2) in Table 4. For all reported distances (2, 3, 5, 7, and 10 miles), all the coefficients of interest are statistically significant and have the same sign as in the baseline specification. We find that the estimated impact of Kaiser is generally mitigated as the distance increases, but our main result—that high ΔWTP_{ij} hospitals negotiate higher prices and lower ΔWTP_{ij} hospitals negotiate lower prices when Kaiser is more competitive—is robust. For example, as noted above, the average effect of increasing the share of a hospital's patients within 3 miles of a Kaiser hospital by 10% is a price increase of \$299 for hospitals above the 95th percentile of ΔWTP_{ij}. The corresponding effects are price increases of \$35 and \$6 when the distances are 5 and 7 miles, respectively. Similarly, the average effect for hospitals above the 25th percentile is a price reduction of \$400 at 3 miles, and \$242 and \$81 at 5 and 7 miles, respectively.

Drive Times. Table 6 reports results where we use a different measure of distance: the drive time from the patient's zipcode to the hospital.[29] We consider drive times between 10 minutes and

[29]Drive times are computed by Google from the centroid of each zipcode to each hospital.

Table 6: Price Regressions with Drive Times

	(1) 10 mins	(2) 15 mins	(3) 20 mins	(4) 25 mins	(5) 30 mins
ΔWTP_{ij}	44.39***	42.39***	33.93***	15.31	17.98
	(6.871)	(7.119)	(10.65)	(16.66)	(16.21)
$Cost_{ij}$	0.395***	0.291***	0.290***	0.399***	0.362***
	(0.111)	(0.107)	(0.0975)	(0.0993)	(0.106)
$\Delta Pmt_{j\setminus ij}$	-0.493***	-0.554***	-0.601***	-0.595***	-0.611***
	(0.0835)	(0.0818)	(0.0696)	(0.0688)	(0.0697)
$Pmt_{j\setminus ij}$	-0.00484	-0.0183	-0.0435**	-0.0464**	-0.0251
	(0.0179)	(0.0181)	(0.0199)	(0.0216)	(0.0215)
$Kaiser_i$	-154.7**	-86.17***	-46.09***	-27.12**	-11.93
	(71.07)	(27.19)	(14.90)	(13.17)	(12.78)
$Kaiser_i * Pmt_{j\setminus ij}$	0.423**	0.243***	0.123***	0.0643	0.0212
	(0.203)	(0.0826)	(0.0469)	(0.0432)	(0.0408)
$Kaiser_i * \Delta WTP_{ij}$	474.7**	321.8***	185.3***	202.8***	163.7***
	(234.3)	(119.1)	(45.43)	(35.81)	(35.63)
$Kaiser_i * \Delta WTP_{ij} * Pmt_{j\setminus ij}$	-1.553***	-0.925***	-0.554***	-0.600***	-0.480***
	(0.599)	(0.286)	(0.116)	(0.107)	(0.103)
Observations	233	233	233	233	233

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: GMM results for regression equation (7), instrumenting for all price terms, where $Kaiser_i$ is the share of hospital i's patients who live within x minutes' drive time of a Kaiser hospital. Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

30 minutes. The results in every specifcation are comparable to the main specification in that the Kaiser coefficient is again negative and significant, and its interaction with ΔWTP_{ij} positive and significant.[30] As with our linear distance measures, the magnitude of Kaiser's impact on price is generally mitigated as drive times increase. Finally, we find that for most drive times, our main results hold: increasing the share of a hospital's patients who live within a 15 minute drive time of a Kaiser hospital by 10%, for example, leads to an average price reduction of \$58 or \$37 for hospitals above the 25th or 50th percentile of ΔWTP_{ij}. For hospitals above the 95th and 99th percentile, prices increase by \$6 and \$161, respectively.

Other Robustness Tests. Table 7 reports the results of several other robustness tests. The first column contains estimates from the baseline model specification using hospital prices from all 14 HSAs (i.e., not omitting LA, SF, and Oakland); this provides 341 hospital-insurer observations, representing 213 unique hospitals. Our finding that the impact of Kaiser is most positive for

[30]Our results are also robust to using drive distances, again computed by Google, instead of drive times.

Table 7: Additional Robustness Tests

	(1) All Mkts	(2) 95 Kaiser	(3) Systems
ΔWTP_{ij}	48.61***	49.98***	46.31***
	(7.170)	(5.971)	(5.399)
$Cost_{ij}$	0.266***	0.292***	0.397***
	(0.0580)	(0.0988)	(0.0995)
$\Delta Pmt_{j\setminus ij}$	-0.515***	-0.493***	-0.459***
	(0.0573)	(0.0771)	(0.0725)
$Pmt_{j\setminus ij}$	0.00171	0.000902	0.00520
	(0.0166)	(0.0186)	(0.0184)
(3mi) $Kaiser_i$	-103.4*	-155.4**	-146.1**
	(56.35)	(72.87)	(61.27)
(3mi) $Kaiser_i * Pmt_{j\setminus ij}$	0.274*	0.408*	0.389**
	(0.159)	(0.211)	(0.175)
(3mi) $Kaiser_i * \Delta WTP_{ij}$	713.9***	1018.5***	1049.7***
	(174.9)	(182.6)	(145.3)
(3mi) $Kaiser_i * \Delta WTP_{ij} * Pmt_{j\setminus ij}$	-1.561***	-2.697***	-2.795***
	(0.417)	(0.511)	(0.414)
$\sum_{h\in\mathcal{S}_i\setminus i} P_{hj}$			-0.0125
			(0.0102)
$\sum_{h\in\mathcal{S}_i\setminus i} Cost_{hj}$			0.0501**
			(0.0238)
Observations	341	233	233

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Columns (1)-(2) report GMM results for regression equation (7), and Column (3) reports GMM results for regression equation (10) (in the Appendix). All specifications instrument for all price terms, where $Kaiser_i$ is the share of hospital i's patients who live within 3 miles of a Kaiser hospital. Column (1) includes all HSAs in CA; Column (2)-(3) omits LA, SF, and Oakland HSAs. Column (2) uses only Kaiser hospitals opened prior to 1995 in defining distance measures. Column (3) allows hospital systems to bargain jointly, and redefines terms $\Delta Pmt_{j\setminus ij}$, $Pmt_{j\setminus ij}$, and ΔWTP_{ij} to reflect that disagreement between hospital i and MCO j results in all hospitals in i's system (denoted $\mathcal{S}_i$) being removed from j's network. Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

the highest ΔWTP hospitals is robust to this change in sample. However now the estimated distribution of the insurer competition effect is shifted up relative to the baseline specification. The estimates imply that increasing exposure to Kaiser by 10% leads to an average price reduction for very low-ΔWTP_{ij} hospitals; the average effect for hospitals above the 10th percentile of ΔWTP_{ij} is a price reduction of \$304. However the same increase in Kaiser exposure leads to an average price increase of \$232 for hospitals above the 50th percentile of ΔWTP_{ij}, and an increase of \$429 for those above the 95th percentile of ΔWTP_{ij}. We surmise this may be due to consumers in the markets we added being more willing to switch to Kaiser upon losing access to a hospital, thereby emphasizing the positive outside option effect of bargaining when we include these urban markets. This difference in consumer behavior could be due to Kaiser's longer history in LA, SF, and Oakland, which may generate greater consumer familiarity with its insurance products. Alternatively, Kaiser's greater attractiveness may be due to its higher density of hospitals and facilities in these markets, providing enrollees with access to multiple Kaiser locations.

To account for the possibility that recently opened Kaiser hospitals might have located based on demand shocks that could influence hospital prices, column 2 of Table 7 repeats our analysis using $Kaiser_i$ variables constructed from locations of Kaiser hospitals active in 1995. As discussed in Section 3.6, using lagged locations would be appropriate if current demand unobservables could not be anticipated more than a decade in advance. There were 26 active Kaiser hospitals in 1995 and 25 of these were active in both 1995 and 2004.[31] Column (2) of Table 7 reports the results of this robustness test using the same (3 mile) definition of Kaiser proximity as before. The estimates imply very similar effects to our main specification. The average effect of increasing proximity to Kaiser by 10% is a price reduction of \$124 for hospitals above the 50th percentile of ΔWTP_{ij}, and an average price increase of \$249 for those above the 95th percentile of ΔWTP_{ij}.

Our final robustness test allows for the possibility that hospitals jointly negotiate as part of a system, and that disagreement between an MCO and a hospital system $\mathcal{S}$ results in all hospitals in that system being removed from the MCO's network. If this is the case, misspecification of the outside options in our baseline bargaining model might bias our main findings. In Section B of the Appendix, we discuss how the model in Section 2 can be modified to allow for hospital systems jointly negotiating with insurers, and we derive a regression equation similar to (7). The main differences require (i) redefining terms $\Delta Pmt_{j\setminus ij}$, $Pmt_{j\setminus ij}$, and ΔWTP_{ij} to reflect that disagreement between hospital i and MCO j results in all hospitals in i's system (denoted $\mathcal{S}_i$) being removed from j's network; and (ii) including two additional terms, $\sum_{h\in\mathcal{S}_i\setminus i} P_{hj}$ and $\sum_{h\in\mathcal{S}_i\setminus i} Cost_{hj}$, to control for the reduction in profits of other hospitals in hospital i's system if i and j come to a disagreement. Using the same logic as our other price instruments, we instrument for $\sum_{h\in\mathcal{S}_i\setminus i} P_{hj}$ using $\sum_{h\in\mathcal{S}_i\setminus i} \Delta WTP_{hj}$.

Results from this specification are reported in column (3) of Table 7. Adding the impact of negotiating as a system changes our estimates very little. The coefficients on ΔWTP_{ij}, $Kaiser_i$ and the interaction term, in particular, are statistically indistinguishable from those in column (2) of Table 4. The other estimated coefficients are also very similar. The estimates imply that the average effect of increasing proximity to Kaiser by 10% is a price reduction of \$73 for hospitals above the 50th percentile of ΔWTP_{ij}, and a price increase of \$256 for those above the 95th percentile of ΔWTP_{ij}.

[31] One facility was converted into medical offices only by 2004, and two had opened.

5 Discussion

Our estimates in all specifications indicate that insurance competition from Kaiser affects negotiated hospital prices in an economically significant way. The average price impact is negative for most hospitals but positive for the most attractive hospitals (as measured by ΔWTP_{ij}).

One potential explanation for our findings is that stronger competition leads to greater premium reductions among insurers, thereby shrinking the surplus to be divided between insurer and hospitals and lowering hospital prices.[32] However, for the most attractive hospitals, Kaiser's impact on an insurer's loss in enrollment when a hospital is dropped outweighs this negative premium effect. While less attractive hospitals may be inframarginal for most consumers—for example, dropping them from a network may not change most consumers' choice of insurer, even if they live near a Kaiser hospital—this may not be the case for the most attractive hospitals, as an insurer may lose a large share of its patients if it competes closely with Kaiser and one of the best hospitals leaves its network.[33,34]

To further unpack the mechanism through which Kaiser and insurer competition influence negotiated prices, we would ideally wish to explicitly model the impact of insurer competition on the pass-through of hospital prices. This is an additional effect of insurer competition, and capturing it in the bargaining model would require relaxing our maintained assumption that premiums do not respond to small changes in negotiated prices: that is, $\partial \phi_k / \partial p_{ij} \approx 0$. Unfortunately, if we explicitly account for the influence of the pass-through of negotiated prices on premiums, we can no longer separate the price paid by MCO j to hospital i from other terms in the bargaining first order condition in (2). Thus, including this effect would require a different approach than the straightforward regression analysis used here. However, this effect is captured in our empirical analysis. Insofar as there is a negative impact of insurer competition on the ability of insurers to pass hospital price increases through to premiums, this effect will also be picked up in the estimated Kaiser coefficient in our equation. This is still consistent with our interpretation that Kaiser's impact on prices occurs via the insurer competition channel, with any negative impact occurring through Kaiser's negative effect on premiums (both reducing the change in the insurer's revenues when a hospital is dropped—the main effect we have discussed—and also the pass-through effect). Thus, the overall effect of Kaiser, as interpreted through the recovered regression coefficients, still provides information on whether, for particular types of hospitals, the negative effect of insurer competition on premiums outweighs other effects and consequently depresses negotiated input

[32] That is, since premium competition is already fiercer in markets where Kaiser is present, the change in insurer revenues upon losing a hospital (term (i) in equation (3)) may be smaller.

[33] This is consistent with the existence of switching costs for consumers across insurers.

[34] We also note two reasons why competition from Kaiser, in particular, could have a smaller or more negative effect on prices than competition from other insurers. First, by considering Kaiser rather than a different insurer, we lose the effect of consumers switching plans specifically in order to access a particular hospital that has been dropped from their plan's network. Instead a potentially smaller number of enrollees may switch because, given that they cannot access that hospital, they prefer to choose an entirely different insurer and set of providers. Second, since the hospital loses patients who switch to Kaiser, it is also worse off if it is dropped from the Blue Shield network. This might not be the case if we considered a different insurer which itself had a contract with the relevant hospital.

prices.

6 Concluding Remarks

This paper specifies a theoretical model of hospital-insurer bargaining that allows consumers to switch insurers in response to the removal of hospitals from an insurer's network. We use this model to develop a price regression equation and estimate it using claims data that contains actual prices paid to hospitals. Our results provide strong evidence that realized prices are consistent with the bargaining theory: almost every term in the equation has the expected sign, and most are statistically significant. They also demonstrate that insurer competition to attract enrollees has a substantial and heterogeneous impact on hospital prices. Though most hospitals negotiate lower prices when Kaiser is present and offers services nearby, very attractive hospitals (as measured by their expected utility contribution to an insurer's network) are able to extract higher payments.

These findings have clear implications for hospital incentives. Hospitals benefit more from consolidation and from investing in services that are attractive to consumers when insurers are less concentrated and more competitive. Our results also imply that, contrary to the arguments made by industry commentators and by some providers, very attractive hospitals may be able to negotiate high prices even in markets with many insurers. In fact, equilibrium negotiated prices for such hospitals can be the highest when insurer competition is the most fierce. We conclude that policy promoting competition between health insurers should take into account the potential impact on negotiated prices with providers and, in particular, exercise caution in markets with highly concentrated or extremely desirable health providers.

References

Capps, Cory, David Dranove, and Mark Satterthwaite, "Competiton and Market Power in Option Demand Markets," *RAND Journal of Economics*, 2003, *34* (4), 737–763.

Chipty, Tasneem and Christopher M. Snyder, "The Role of Firm Size in Bilateral Bargaining: A Study of the Cable Television Industry," *Review of Economics and Statistics*, 1999, *81* (2), 326–340.

Collard-Wexler, Allan, Gautam Gowrisankaran, and Robin S. Lee, "Bargaining in Bilateral Oligopoly: An Alternating Offers Representation of the "Nash-in-Nash" Solution," 2013. Unpublished.

Crawford, Gregory S. and Ali Yurukoglu, "The Welfare Effects of Bundling in Multichannel Television," *American Economic Review*, 2012, *102* (2), 643–685.

Dafny, Leemore S., "Are Health Insurance Markets Competitive?," *American Economic Review*, 2010, *100* (4), 1399–1431.

— , **Kate Ho, and Mauricio Varela**, "Let Them Have Choice: Gains from Shifting Away from Employer-Sponsored Health Insurance Towards an Individual Exchange," *American Economic Journal: Economic Policy*, 2013, *5* (1), 32–58.

— , **Mark Duggan, and Subramaniam Ramanarayanan**, "Paying a Premium on Your Premium? Consolidation in the U.S. Health Insurance Industry," *American Economic Review*, 2012, *102* (2), 1161–1185.

Dranove, David, Mark Satterthwaite, and Andrew Sfekas, "Boundedly Rational Bargaining in Option Demand Markets: An Empirical Application," 2008. mimeo.

Ellison, Sara F. and Christopher M. Snyder, "Countervailing Power in Wholesale Pharmaceuticals," *Journal of Industrial Economics*, 2010, *58* (1), 32–53.

Farrell, Joseph, David J. Balan, Keith Brand, and Brett W. Wendling, "Economics at the FTC: Hospital Mergers, Authorized Generic Drugs, and Consumer Credit Markets," *Review of Industrial Organization*, 2011, *39*, 271–296.

Galbraith, John K., *American Capitalism: The Concept of Countervailing Power*, Boston: Houghton Mifflin, 1952.

Gowrisankaran, Gautam, Aviv Nevo, and Robert Town, "Mergers When Prices Are Negotiated: Evidence from the Hospital Industry," 2013. Unpublished.

Grennan, Matthew, "Price Discrimination and Bargaining: Empirical Evidence from Medical Devices," *American Economic Review*, 2013, *103* (1), 147–177.

Ho, Katherine, "The Welfare Effects of Restricted Hospital Choice in the US Medical Care Market," *Journal of Applied Econometrics*, 2006, *21* (7), 1039–1079.

— , "Insurer-Provider Networks in the Medical Care Market," *American Economic Review*, 2009, *99* (1), 393–430.

Horn, Henrick and Asher Wolinsky, "Bilateral Monopolies and Incentives for Merger," *RAND Journal of Economics*, 1988, *19* (3), 408–419.

Inderst, Roman and Christian Wey, "Bargaining, Mergers, and Technology Choice in Bilaterally Oligopolistic Industries," *RAND Journal of Economics*, 2003, *34* (1), 1–19.

Lee, Robin S. and Kyna Fong, "Markov Perfect Network Formation: An Applied Framework for Bilateral Oligopoly and Bargaining in Buyer-Seller Networks," 2012. Unpublished.

Lewis, Matthew S. and Kevin E. Pflum, "Diagnosing Hospital System Bargaining Power in Managed Care Networks," 2013. Unpublished.

Melnick, Glenn A., Yu-Chu Shen, and Vivian Yaling Wu, "The Increased Concentration of Health Plan Markets Can Benefit Consumers Through Lower Hospital Prices," *Health Affairs*, 2010, *30* (9), 1728–1733.

Moriya, Asako S., William B. Vogt, and Martin Gaynor, "Hospital Prices and Market Structure in the Hospital and Insurance Industries," *Health Economics, Policy and Law*, 2010, *5* (459–479).

Sorensen, Alan T., "Insurer-Hospital Bargaining: Negotiated Discounts in Post-Deregulation Connecticut," *Journal of Industrial Economics*, 2003, *51* (4), 469–490.

Stole, Lars A. and Jeffrey Zweibel, "Intra-Firm Bargaining under Non-Binding Contracts," *Review of Economic Studies*, 1996, *63* (3), 375–410.

Town, Robert J. and Gregory Vistnes, "Hospital Competition in HMO Networks," *Journal of Health Economics*, 2001, *20*, 733–753.

A Demand Estimation: Further Details

Our consumer demand model is outlined in Section 3.2. We follow the method in Ho (2006), estimating demand for hospitals using a discrete choice model that allows for observed differences across consumers.

We define 5 diagnosis categories using ICD-9-CM codes and MDC (Major Diagnosis Category) codes, as shown in Table 8. The categories are cardiac, cancer, labor, digestive diseases, and neurological diseases. The sixth category, 'other diagnoses,' includes all other categories in the data other than newborn babies (defined as events with MDC 15 where the patient is less than 5 years old). The hospital 'service' variables are defined using American Hospital Association data for 2003-2004 (if observations are missing for a particular hospital in one year we fill them in from the other). These variables summarize the services offered by each hospital; they cover cardiac, imaging, cancer, and birth services. Each hospital is rated on a scale from 0 to 1, where 1 implies that the hospital offers the least common of a list of relevant services and 0 implies that it offers none of the services. Details are given in Table 9.

Table 8: Definition of Diagnosis Categories

Category	MDC or ICD-9-CM codes
Cardiac	MDC: 05 (and not cancer)
	ICD-9-CM: 393-398; 401-405; 410-417; 420-249
Cancer	ICD-9-CM: 140-239
Neurological	MDC: 19-20
	ICD-9-CM: 320-326; 330-337; 340-359
Digestive	MDC: 6 (and not cancer or cardiac)
	ICD-9-CM: 520-579
Labor	MDC 14-15 (and aged over 5)
	ICD-9-CM: 644; 647; 648; 650-677; V22-V24; V27

Notes: Patient diagnoses were defined using MDC codes in the admissions data where possible. In other cases, supplemental ICD-9-CM codes were used.

Table 9: Definition of Hospital Services

Cardiac	Imaging	Cancer	Births
CC laboratory	Ultrasound	Oncology services	Obstetric care
Cardiac IC	CT scans	Radiation therapy	Birthing room
Angioplasty	MRI		
Open heart surgery	SPECT		
	PET		

Notes: The exact methodology for rating hospitals is as follows. If the hospital provides none of the services, its rating = 0. If it provides the least common service, its rating = 1. If it offers some service X but not the least common service its rating = (1 - x) / (1 - y), where x = the percent of hospitals offering service X and y = the percent of hospitals offering the least common service.

There is no outside option, since our data includes only patients who are sick enough to go to hospital for a particular diagnosis. We estimate the model using standard maximum likelihood techniques and our micro (encounter-level) data. We observe the network of each insurer and, therefore, can accurately specify the choice set of each patient. We assume that the enrollee can choose any hospital in his HSA that is included in his insurer's network provided that hospital is located no more than 100 miles from the patient's home zip code.

Table 10 shows the results of the hospital demand specification (omitting hospital fixed effects due to space constraints). The results are in line with Ho (2006) and the previous hospital choice literature. The coefficient on distance is negative and that on distance squared is positive, with very similar magnitudes to those in Ho (2006). The non-interacted effects of teaching hospitals and other hospital characteristics are absorbed in the fixed effects; however, the interactions show that patients with very complex conditions (cancer and neurological diseases) attach the highest positive weight to teaching hospitals. Many of the interactions are difficult to interpret, but it is clear that patients with cardiac diagnoses place a strong positive weight on hospitals with good cardiac services, cancer patients on those with cancer services (although, as in Ho (2006), this coefficient is not significant at p=0.1), and women in labor on hospitals with good birthing services.

B Hospital System Bargaining

We adapt our model to allow for the possibility that hospitals bargain jointly, as part of hospital systems. Let $\mathcal{S}$ denote the set of hospital systems, and for some system $s \in \mathcal{S}$, let $\mathcal{S}_s$ denote the set of hospitals that belong to system s. Let profits for a hospital system s be denoted by:

$$\pi_{s,\mathcal{S}}(\boldsymbol{p}, \mathcal{G}) = \sum_{n \in \mathcal{G}_i} \sum_{h \in \mathcal{S}_s} D_n(\boldsymbol{\phi}(\boldsymbol{p}, \mathcal{G}), \mathcal{G}) \sigma_{hn}(\mathcal{G})(p_{hn} - c_{hn})$$

We assume each hospital system s and insurer j negotiates prices via simultaneous bilateral Nash bargaining so that, as before, each price $\{p_{ij}\}_{i \in \mathcal{S}_s}$ maximizes the Nash product of system and insurer profits:

$$\begin{aligned} p_{ij} \in \arg\max\, & [\pi_{j,\mathcal{M}}(\boldsymbol{p}, \mathcal{G}) - \pi_{j,\mathcal{M}}(\boldsymbol{p}_{-sj}, \mathcal{G} \setminus \{hj\}_{h \in \mathcal{S}_s})]^{\tau_M} \\ & \times [\pi_{s,\mathcal{S}}(\boldsymbol{p}, \mathcal{G}) - \pi_{s,\mathcal{S}}(\boldsymbol{p}_{-sj}, \mathcal{G} \setminus \{hj\}_{h \in \mathcal{S}_s})]^{\tau_H} \;\; \forall ij \in \mathcal{G}, i \in \mathcal{S}_s \end{aligned} \tag{8}$$

This is the corresponding bargain as (8), except the disagreement point represents insurer j losing all hospitals in system s.

In a slight abuse of notation, let $\mathcal{S}_i$ denote the set of hospitals that belong to the same system

Table 10: Demand System Estimates

Interaction Terms	Variable	Parameter	Std. Err.
	Distance (miles)	-0.162^{***}	0.001
	Distances squared	0.000^{***}	0.000
Interactions: Teaching	Income ($000)	0.002	0.002
	PPO enrollee	0.128^{*}	0.069
	Cancer	0.136	0.106
	Cardiac	-0.270^{***}	0.080
	Digestive	-0.163^{*}	0.094
	Labor	0.125	0.097
	Neurological	1.306^{***}	0.172
Interactions: Nurses Per Bed	Income ($000)	0.000	0.001
	PPO enrollee	-0.090^{**}	0.037
	Cancer	0.131^{**}	0.058
	Cardiac	-0.154^{***}	0.044
	Digestive	-0.106^{**}	0.047
	Labor	-0.218^{***}	0.049
	Neurological	-1.029^{***}	0.107
Interactions: For-Profit	Income ($000)	0.001	0.001
	PPO enrollee	0.021	0.052
	Cancer	0.012	0.084
	Cardiac	-0.144^{**}	0.059
	Digestive	-0.125^{*}	0.067
	Labor	0.284^{***}	0.064
	Neurological	0.571^{***}	0.114
Interactions: Cardiac Services	Income ($000)	-0.002	0.001
	PPO enrollee	0.381^{***}	0.049
	Cardiac	0.370^{***}	0.053
Interactions: Imaging Services	Income ($000)	0.007^{***}	0.002
	PPO enrollee	0.186^{***}	0.061
	Cancer	0.138	0.091
	Cardiac	-0.036	0.072
	Digestive	0.026	0.066
	Labor	-0.404^{***}	0.070
	Neurological	-0.616^{***}	0.134
Interactions: Cancer Services	Income ($000)	-0.012^{***}	0.004
	PPO enrollee	0.072	0.130
	Cancer	0.291	0.225
Interactions: Labor Services	Income ($000)	0.007^{***}	0.001
	PPO enrollee	-0.336^{***}	0.054
	Labor	1.026^{***}	0.068
	Hospital Fixed Effects	Yes	
	Pseudo-R2	0.528	

Notes: Maximum likelihood estimation of demand for hospitals using a multinomial logit model. Specification includes hospital fixed effects. N = 850,073 across 35,289 admissions.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

as hospital i. Then for each hospital $i \in \mathcal{S}_i$, the FOC of (8) can be expressed as:

$$\underbrace{p^*_{ij}\sigma_{ij}}_{\text{hospital price / enrollee}} = \tau_H \left[\underbrace{\left(\frac{D_j\phi_j - \tilde{D}_j\tilde{\phi}_j}{D_j} \right)}_{\text{(i) } \Delta \text{ MCO revenues}} - \underbrace{\left(\sum_{h \in \mathcal{G}_j \setminus \{lj\}_{l \in \mathcal{S}_i}} p^*_{hj}(\sigma_{hj} - \tilde{\sigma}_{hj} + \frac{D_j - \tilde{D}_j}{D_j}\tilde{\sigma}_{hj}) \right)}_{\text{(ii) } \Delta \text{ MCO } j \text{ payments to other hospitals not in } \mathcal{S}_i} \right]$$
$$+ \tau_M \left[\underbrace{\bar{c}_i\sigma_{ij}}_{\text{(iii) hospital costs / enrollee}} - \underbrace{\sum_{n \in \mathcal{G}_i \setminus ij} \sum_{h \in \mathcal{S}_i} \frac{(D_n\sigma_{hn} - \tilde{D}_n\tilde{\sigma}_{hn})}{D_j}(p^*_{hn} - \bar{c}_h)}_{\text{(iv) } \Delta \text{ System } \mathcal{S}_i \text{ profits from other MCOs}} \right]$$
$$- \underbrace{\sum_{h \in \mathcal{S}_i \setminus i} \sigma_{hj}\left[p_{hj} - \tau_M\bar{c}_h\right]}_{\text{(v) Loss in profits of other system hospitals from MCO } j} + \epsilon_{ij} \tag{9}$$

where now $\tilde{(\cdot)}$ represents the value of functions that take as arguments $\mathcal{G} \setminus \mathcal{S}_i$: that is, the outcome if MCO j and system $\mathcal{S}_i$ come to a disagreement and all hospitals $h \in \mathcal{S}_i$ are no longer on j's network. Term (v) is new and represents the profits of other hospitals in $\mathcal{S}_i$ that are obtained from MCO j, but would be lost if $\mathcal{S}_i$ and MCO j came to a disagreement.

Finally, note that this expression is equivalent to (3), if there were no hospital systems (or hospitals bargained independently).

Estimation. Informed by the FOCs given by (9), we modify our estimation equation (7) to account for systems as follows:

$$\begin{aligned}
\underbrace{P_{ij}}_{\hat{p}_{ij}\hat{\sigma}_{ij}} = \; & \alpha_1 \underbrace{\text{Cost}_{ij}}_{\bar{c}_i\hat{\sigma}_{ij}} + \alpha_2 \underbrace{\Delta Pmt_{j,\setminus\mathcal{S}_i j}}_{\sum_{h \in \mathcal{G}_j \setminus \{lj\}_{l \in \mathcal{S}_i}} \hat{p}_{hj}(\hat{\sigma_{hj}} - \hat{\tilde{\sigma}}_{hj})} \\
& + \alpha_3 \Delta WTP_{\mathcal{S}_i j} + \alpha_4 Kaiser_i + \alpha_5 Kaiser_i \times \Delta WTP_{\mathcal{S}_i j} \\
& + \underbrace{Pmt_{j,\setminus\mathcal{S}_i j}}_{\sum_{h \in \mathcal{G}_j \setminus \{lj\}_{l \in \mathcal{S}_i}} \hat{p}_{hj}(\hat{\tilde{\sigma}}_{hj})} \left[\alpha_6 + \alpha_7 Kaiser_i + \alpha_8 Kaiser_i \times \Delta WTP_{\mathcal{S}_i j}\right] \\
& + \alpha_9 \sum_{h \in \mathcal{S}_i \setminus i} P_{hj} + \alpha_{10} \sum_{h \in \mathcal{S}_i \setminus i} Cost_{hj} \\
& + \boldsymbol{HSA}_m + BS_j + \boldsymbol{\beta} \times \boldsymbol{demogs}_i + \varepsilon_{ij}.
\end{aligned} \tag{10}$$

where: $Pmt_{j,\setminus\mathcal{S}_i j}$ and $\Delta Pmt_{j,\setminus\mathcal{S}_i j}$ are modified to consider the outcome when the whole system $\mathcal{S}_i$ is dropped from j's network, $\Delta WTP_{\mathcal{S}_i j}$ represents the change in consumers' WTP for MCO j's network when the whole system $\mathcal{S}_i$ is dropped, and terms $\sum_{h \in \mathcal{S}_i \setminus i} P_{hj}$ and $\sum_{h \in \mathcal{S}_i \setminus i} Cost_{hj}$ are added to control for term (v) in (9).

Results are reported in column 4 of Table 7 in the main text.

Table 11: Kaiser Hospitals

Hospital Name	History
ANAHEIM MEDICAL CENTER (MC)	Bought in 1979 (previously the Canyon General Hospital).
BALDWIN PARK MC†	Built in 1994, although not utilized until 1998.
BELLFLOWER MEDICAL OFFICES	Built in 1966.
FONTANA MC	Newly constructed in 1954 to replace an old facility.
FRESNO MC	Opened in 1985 as a Kaiser Permanente physician clinic. Became a hospital in 1995.
HAYWARD MC	Built in the 1960s.
LOS ANGELES MC	Built in the 1950s
MANTECA MC†	Bought in 2004 (previously St. Dominic's Hospital).
OAKLAND MC	Opened in 1950.
PANORAMA CITY MC	Built in 1962.
REDWOOD CITY MC	Opened in 1952.
RICHMOND MC	Built in 1995; replaced Kaiser Richmond Field Hospital (built in 1942) which was deemed seismically unsafe.
RIVERSIDE MC	Built in 1989.
SACRAMENTO MC	Built in 1965, expanded in 1970.
SAN DIEGO MC	Built in 1972.
SAN FRANCISCO MC	Built in 1950s (together with Los Angeles Medical Center).
SAN JOSE MC	Bought in 1976 (previously Santa Teresa Hospital and Medical Center).
SAN RAFAEL MC	Bought in 1976 (previously Terra Linda Valley Convalescent Hospital).
SANTA CLARA MC	Built in 1967. Moved to new local facility in 2007.
SANTA ROSA MEDICAL OFFICES	Built before 1980.
SOUTH BAY MC	Built in 1950.
SOUTH SACRAMENTO MC	Medical office opened in 1984, the hospital followed in 1985.
SOUTH SAN FRANCISCO MC	Reconstructed in 1974 to replace and expand the previous Kaiser community hospital.
VALLEJO MC	Built in 1972 to replace the old Vallejo Community Hospital (which was bought by Kaiser in 1947).
WALNUT CREEK MC	Built in 1953.
WEST LOS ANGELES MC	Constructed in 1970s; opened in 1974 to serve West LA, Santa Monica Bay, and part of South Bay area.
WOODLAND HILLS MC	Built in 1986.

Notes: Estimated entry dates of 27 Kaiser hospitals active in 2004 that are used in our analysis. Sources available upon request. † represents hospitals that were not owned by Kaiser or active in 1995.

C Kaiser Hospitals

Table 11 lists the names and brief histories of the 27 Kaiser hospitals active in California in 2004 that are used in our analysis.