Insurer Competition and Negotiated Hospital Prices*

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Abstract

We measure the impact of increased health insurer competition on negotiated hospital prices using detailed 2004 California claims data. We develop a theoretical bargaining model to motivate our empirical analysis, and use the competitiveness of Kaiser Permanente, a large vertically integrated insurer, in a hospital's market as a measure of insurer competition. We find that increasing competition reduces hospital prices on average, but that the most attractive hospitals can leverage increased competition to negotiate higher rates. This bargaining effect creates incentives for further hospital consolidation and implies that hospital market power can impact prices even in markets with many insurers.

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

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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 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] Commentators and hospital executives have argued that this competition at the insurer level may also reduce insurer payments to hospitals: since increased insurer competition may reduce industry surplus by constraining premiums and insurers' ability to recoup rate increases, it may generate a downward pressure on hospital prices.[2] This in turn may help constrain the growth of annual U.S. hospital spending—which, at $900 billion, accounted for over 30% of the $2.8 trillion in total national healthcare expenditures in 2012 (Cuckler et al., 2013).

However, the argument that insurer competition necessarily leads to lower hospital prices 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. Our focus is on negotiated hospital prices since they affect consumer surplus through their impact on insurer premiums. In addition, changes in these prices—i.e., 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.

Previous papers have found evidence that supports each of the potential effects of insurer

[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.

[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).

competition. Dafny, Duggan and Ramanarayanan (2012) find that greater insurer concentration resulting from a merger of insurers is associated with a modest increase in premiums; Dafny (2010) finds evidence consistent with this. Other papers suggest that negotiated hospital prices can rise in response to increased insurer competition (e.g., Moriya, Vogt and Gaynor (2010), Melnick, Shen and Wu (2010)). Our study accounts for both effects, emphasizing the potential heterogeneous impact of insurer competition across different hospitals. We initially hypothesize that the most attractive hospitals 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 downward pressure on premiums caused by insurer competition outweighs the offsetting bargaining effect. Both theoretically and empirically, such heterogeneity is crucial to consider and, to our knowledge, has not been examined in the previous literature. Our analysis thus furthers our understanding of the determinants of provider markups in the healthcare industry, which are the source of over 60% of the observed variation in commercial health spending across U.S. regions (Newhouse et al., 2013).

We begin by developing a theoretical model of bargaining between hospitals and insurers. This formalizes our intuition regarding the effects of interest. It also motivates our main regression specification relating negotiated prices to measures of insurer competition, and absent unlimited data, disciplines the regressors and functional forms that are employed. The model predicts 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 reimbursements from other insurers. Several of our regressors must therefore 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, relating 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 represent 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 (the vast majority 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 U.S., 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. In contrast, measures based on consumer proximity to other insurers would be harder to interpret since these insurers often have their own contracts with the hospital in question, and therefore may affect the bargaining process through multiple channels. 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 hospital's patients who live within 3 miles of a Kaiser Permanente hospital as our primary measure of insurer competition for a given hospital-insurer bargain. This variable captures the extent to which consumers may switch insurers to Kaiser if that hospital is dropped from a network. The intuition is as follows: if an insurer, such as Blue Shield (BS), loses a hospital from its network, BS may see a greater reduction in enrollment (and therefore a greater reduction in its outside option) 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, and reduces BS's outside option in bargaining. 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.

As our theoretical bargaining model makes clear, competition between an insurer and Kaiser may also affect negotiated prices through other channels. 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.[3] This tends to reduce hospital prices. Furthermore, we might expect Kaiser's presence to have a more negative effect on prices than competition from other insurers because Kaiser has a more adverse effect on an hospital's outside option. For example, consumers who otherwise may have switched to an alternative insurer (which contracted with the hospital in question) when the hospital was dropped from an insurer's network, may now switch to Kaiser instead and thus no longer be able to visit the hospital. Overall, the net impact of Kaiser competition on prices is theoretically ambiguous, and may vary across hospitals.[4,5]

[3] Increased insurer competition may also limit an insurer's ability to charge higher premiums to offset rate increases.

[4] Kaiser may have a positive effect on prices for the most attractive hospitals but a negative effect for other hospitals. Consider the following example. If a very attractive hospital (e.g., a "center of excellence") is dropped from BS's network when Kaiser is not present, a large number of consumers may switch from BS to another insurer with a contract with that hospital in order to access it. Adding Kaiser to the market may not harm the attractive hospital's outside option: most of its patients might still switch to the alternative insurer if it is dropped, rather than to Kaiser, perhaps viewing Kaiser hospitals as a poor substitute for the center of excellence. However, the remaining marginal BS enrollees, who would otherwise have stayed with the plan after losing the attractive hospital, may now switch to Kaiser, thereby harming BS's outside option. This would lead to a positive impact of Kaiser on negotiated prices for the attractive hospital. However, Kaiser may adversely affect a less attractive hospital's outside option as consumers who would have switched to other insurers in order to maintain access to this dropped hospital may now instead choose to switch to Kaiser. Furthermore, there may be fewer consumers who are willing to switch from BS to Kaiser upon BS losing the less attractive hospital. Both of these effects would make the impact on prices less positive or potentially negative.

[5] Note also that if a hospital negotiates with several commercial insurers, the impact of Kaiser's presence on each

We investigate the relative magnitudes of the competing effects by including in our regression a measure of how much consumers value access to a particular hospital on an insurer's network. This measure, developed in the previous literature on hospital-insurer bargaining and computed from the estimated hospital demand system, is the predicted change in consumers' "willingness-to-pay" (ΔWTP) for an insurer's network when a particular hospital is removed from the network (Capps, Dranove and Satterthwaite (2003)).[6] 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. We also include an interaction term between these two variables to disentangle the heterogeneous effects of insurer competition.

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.

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 desirability to consumers that may be correlated with proximity to a Kaiser hospital. Other robustness tests include allowing hospitals to bargain as part of systems, employing alternative regression specifications, and using alternative distance measures or travel times to measure exposure to Kaiser.

Ultimately, we view our approach as a direct way to demonstrate that insurer competition is important; it does not require the more stringent assumptions or demanding data needed to estimate a model of insurer demand and premium-setting. We aim 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

of these individual bilateral bargains will have reinforcing effects across all of them.

[6] 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.

internalize this possibility), then we would not expect to find any impact of our Kaiser competitiveness variable on prices.[7] 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. Furthermore, our analysis suggests that the distribution of rents between insurers and hospitals is heterogeneous and favors more attractive providers, implying even greater incentives for further hospital consolidation as the health insurance market becomes more competitive.

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, Vogt and Gaynor (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, Shen and Wu (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, Dranove and Satterthwaite (2003) estimate the determinants of negotiated hospital prices using specifications motivated by an underlying bargaining model; however, they do not specify the particular bargaining model employed, nor the effect of insurer competition on the bargaining outcome.[8] Gowrisankaran, Nevo and Town (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, Satterthwaite and Sfekas (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 cannot switch plans in response to an insurer network change or bargaining disagreement). This abstraction is primarily made in response to data limitations and

[7] 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 network change.

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

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 (2013) 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, Duggan and Ramanarayanan (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; Dafny (2010) finds evidence consistent with this.[9] 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)).[10]

2 Theoretical Model

In this section we develop a stylized theoretical 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. We rely on the insights from our theoretical model to discipline our empirical approach and provide the basis of our estimating equation. In particular, it informs the set of regressors to be used and the proper functional form of the

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

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

relationship.[11]

2.1 Setup

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 treating one of j's patients.[12] 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 with some probability; those that are sick visit some hospital in their network.[13]

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. 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

[11] An alternative approach would be to proceed with a regression relating prices to a rich set of variables (with interactions and multiple functional forms) controlling for potential demand and cost shifters for each hospital-insurer pair; this approach is infeasible given current data limitations.

[12] For our simple theoretical model, we assume prices take this form. In general, hospital contracts are more complicated than this; we discuss this issue further in our empirical application.

[13] In our empirical application, we will allow for heterogeneous consumers who become sick with different diagnoses with different probabilities. Consumers will also have different preferences for hospitals depending on their diagnosis and type.

hospital to visit, and the quantity and composition of consumer types who visit hospitals are 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).[14] 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. A similar assumption and procedure is used for costs.

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:

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

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 $\boldsymbol{p}_{-ij}$).[15] 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, Nevo and Town (2013), Lee and Fong (2013).[16] 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.[17] 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

[14] This assumption may not be accurate in some cases. For example, Ho and Pakes (2013) find that in California, when referring physicians are given incentives to use low-cost hospitals through capitation payments, the hospital referral is influenced by its price. However the price effect is small or insignificant for the two insurers in our data: Blue Cross PPO (which rarely uses capitation payments for its physicians) and Blue Shield HMO (the only not-for-profit plan in the study's data sample). We therefore abstract away from these patient steering issues.

[15] 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.

[16] Collard-Wexler, Gowrisankaran and Lee (2013) provide a non-cooperative foundation for this bargaining solution in bilateral oligopoly.

[17] 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.

after disagreement) may still be influenced by the degree of insurer competition.

2.2 Simple Case: A Monopolist MCO

Before proceeding with our general analysis, we develop the intuition for how insurer competition affects negotiated prices in a simple setting with only a monopolist MCO j and two hospitals, A and B. In this environment under the assumption of symmetric Nash bargaining (i.e., $\tau_M = \tau_H$) and with costs per admission given by c_A or c_B, we re-express (1) for the bargain between j and A:

$$p^*_{Aj} = \arg\max_p \underbrace{\left[D_j \times (\phi_j - \sigma_{Aj} p - \sigma_{Bj} p_{Bj}) - \tilde{D}_{j\setminus A} \times (\tilde{\phi}_{j\setminus A} - \tilde{\sigma}_{Bj\setminus A} p_{Bj})\right]}_{\text{MCO } j\text{'s "gains from trade"}} \times \underbrace{\left[D_j \sigma_{Aj}(p - c_A)\right]}_{\text{Hospital } A\text{'s "gains from trade"}} \tag{2}$$

where $\tilde{D}_{j\setminus A}$, $\tilde{\phi}_{j\setminus A}$, and $\tilde{\sigma}_{Bj\setminus A}$ denote the values of these objects if MCO j and hospital A did not come to an agreement so that A was no longer on j's network. Since we have assumed MCO j is a monopolist, A's disagreement point (i.e., $\pi_{A,\mathcal{H}}(\boldsymbol{p}_{-Aj}, \mathcal{G} \setminus Aj)$) is equal to 0. We note that even with a monopolist insurer, $\tilde{D}_{j\setminus A} < D_j$ since more consumers may choose to remain uninsured if MCO j drops hospital A.

For simplicity, consider the case where $\sigma_{Aj} = \sigma_{Bj} = 1/2$, and upon disagreement between j and A, all patients enrolled in j visit B (i.e., $\tilde{\sigma}_{Bj\setminus A} = 1$). The first-order condition (FOC) of (2) can then be derived:

$$p^*_{Aj} = \underbrace{\frac{D_j \phi_j - \tilde{D}_{j\setminus A} \tilde{\phi}_{j\setminus A}}{D_j}}_{\text{(i)}} - \underbrace{\frac{p^*_{Bj}(D_j/2 - \tilde{D}_{j\setminus A})}{D_j}}_{\text{(ii)}} + \underbrace{\frac{c_A}{2}}_{\text{(iii)}} \tag{3}$$

There are three terms in (3) that affect negotiated prices. Term (iii) is the easiest to interpret, and reflects the fact that hospital A will obtain higher prices if it has higher costs per enrollee. We discuss terms (i) and (ii) next, and how they are affected by the presence of insurer competition.

Term (i) represents j's changes in premium revenue upon losing hospital A: the greater this term, the higher is hospital A's negotiated price. Since this change can result from both fewer patients being enrolled in j, and lower premiums being charged by j upon disagreement, the impact of increasing insurer competition on this term is ambiguous. If premiums are fixed and do not adjust upon disagreement (i.e., $\phi_j = \tilde{\phi}_{j\setminus A}$), then the entry of a competing insurer is likely to increase term (i) since $D_j - \tilde{D}_{j\setminus A}$ increases when there is a better alternative to the outside option present in a market. However, since insurer competition may increase premium competition, the reduction in j's premiums upon disagreement without insurer competition may actually be *greater* than with insurer competition. If this is the case, then increasing insurer competition may decrease negotiated prices.

Term (ii) represents the change in payments made by j to hospital B as a result of losing A from its network. Since it is likely that $\tilde{D}_{j\setminus A} > D_j/2$ (i.e., MCO j does not lose all of the enrollees that used to visit hospital A), then j's payments to B increase upon disagreement with hospital A.

This implies term (ii) is negative, which (given its negative sign in the equation) means hospital A captures a higher negotiated price the greater is p^*_{Bj}. Insurer competition will then have two effects. The first is a direct effect due to its impact on $(D_j/2 - \tilde{D}_{j\setminus A})/D_j$: if $\tilde{D}_{j\setminus A}$ becomes smaller with insurer competition (so that the numerator becomes less negative or even positive), then insurer competition will have a negative effect on p^*_{Aj}. The second effect is an indirect effect through p^*_{Bj}: depending on whether p^*_{Bj} increases or decreases due to insurer competition, it will have either a reinforcing or dampening effect on p^*_{Aj} (and vice versa).

Thus, even in this simple setting, it is clear that the introduction of insurer competition has the potential to either increase or decrease negotiated prices.

2.3 General Model

We now return to the general model with multiple MCOs and hospitals active in a given market. Following the previous analysis, we take the first-order-condition (FOC) of the maximization problem given by (1), and re-arrange it in order to derive the following linear equation for prices:

$$\begin{aligned}
\underbrace{p^*_{ij}\sigma_{ij}}_{\text{hospital price / enrollee}} =& \tau_H \Bigg[\underbrace{\left(\frac{D_j \phi_j - \tilde{D}_{j\setminus ij}\tilde{\phi}_{j\setminus ij}}{D_j} \right)}_{\text{(i) } \Delta \text{ MCO revenues}} - \underbrace{\left(\sum_{h \in \mathcal{G}_j \setminus ij} p^*_{hj} (\sigma_{hj} - \tilde{\sigma}_{hj\setminus ij} + \frac{D_j - \tilde{D}_{j\setminus ij}}{D_j} \tilde{\sigma}_{hj\setminus ij}) \right)}_{\text{(ii) } \Delta \text{ MCO } j \text{ payments to other hospitals}} \Bigg] \qquad (4) \\
&+ \tau_M \Bigg[\underbrace{\bar{c}_i \sigma_{ij}}_{\text{(iii) hospital costs / enrollee}} - \underbrace{\sum_{n \in \mathcal{G}_i \setminus ij} \frac{(D_n \sigma_{in} - \tilde{D}_{n\setminus ij}\tilde{\sigma}_{in\setminus ij})}{D_j} (p^*_{in} - \bar{c}_i)}_{\text{(iv) } \Delta \text{ Hospital } i \text{ profits from other MCOs}} \Bigg] \\
&+ \epsilon_{ij}
\end{aligned}$$

where, as in the simple example, 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, $\tilde{\phi}_{j\setminus ij} \equiv \phi_j(\boldsymbol{p}_{-ij}, \mathcal{G} \setminus ij)$. 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.[18]

As in the simple case discussed previously, our general model predicts that each MCO j and hospital i bargain over the gains from trade created when that hospital is onboard an MCO's network. These "gains" are obtained by MCOs through higher premiums and additional enrollees; they are shared with hospitals through negotiated prices. We scale both sides of the FOC in (4) by σ_{ij} in in order to obtain a measure of hospital surplus that is comparable across hospitals for a particular MCO: each hospital and insurer split their total gains from trade in a manner that is not

[18] In Section 4.3, we also allow for hospital systems to remove all of their hospitals upon disagreement.

necessarily dependent on the number of admissions that a hospital actually receives, and focusing on a *price-per-enrollee* (represented by $p^*_{ij}\sigma_{ij}$) as opposed to a price-per-admission is consistent with this.[19] We thus focus on (4) as our primary specification (although we also report the estimates from the regression equation implied by an unscaled version of the FOC in the appendix as a robustness check; this had little effect on our overall results).

Finally, $\bar{c}_i$ represents hospital i's average cost of an admission, and ϵ_{ij} represents a function of the deviation from average costs for a given MCO j (defined to be $\omega_{ij} \equiv c_{ij} - \bar{c}_i$) and the following demand parameters:

$$\epsilon_{ij} \equiv \tau_M \left[\omega_{ij}\sigma_{ij} + \sum_{n \in \mathcal{G}_i \setminus ij} \frac{(D_n \sigma_{in} - \tilde{D}_{n\setminus ij}\tilde{\sigma}_{in\setminus ij})}{D_j} \omega_{in} \right] \tag{5}$$

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.[20]

Discussion Equation (4) 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. As in our simple example with a monopolist MCO, term (i) represents j's change in premium revenue upon losing hospital i: as 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. That is, on one 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. On the other hand, a competitive insurance market can reduce the loss in revenues faced by an insurer upon losing a hospital since premium markups are low, implying that losing a hospital leads to only a small adjustment in premiums.

Term (ii) represents the change in payments per enrollee that j makes to other hospitals in its existing network upon losing i, and is a generalized version of term (ii) in equation (3) where we now allow the MCO to have additional hospitals on its network. 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), $\sum_{h \in \mathcal{G}_j \setminus ij} p^*_{hj}((D_j - \tilde{D}_{j\setminus ij})\tilde{\sigma}_{hj})/D_j$, adjusts for the fact that fewer patients are now enrolled in j. Overall, term (ii) indicates that if j's enrollees visit higher-cost

[19]For example, consider two hospitals A and B that deliver the same "gains-from-trade" to MCO j, but A serves fewer patients than B (e.g., it is only valuable for a rare disease or diagnosis so that $\sigma_{Aj} < \sigma_{Bj}$). The model indicates that each hospital obtains the same absolute amount of surplus from MCO j (and also the same price-per-enrollee), but having the RHS (4) divided by σ_{ij} in order to obtain a price-per-admission will obscure this.

[20] We are implicitly assuming away any insurer-hospital specific unobservable profit terms which may affect the initial decision to contract (c.f. Ho (2009); Pakes et al. (2011)). If present, these profit-specific errors would be included in ϵ_{ij}; they would affect our results insofar these terms would be correlated with our measure of insurer competition discussed in the next section. However, given the rich set of controls and profitability measures we employ, we do not believe this to be of concern.

hospitals in j's network if i is dropped, then p^*_{ij} will be higher.

The second line of (4), representing changes to hospital i's gains from trade upon disagreement with MCO j, is also composed of 2 terms. Term (iii) (as before) represents hospital costs per enrollee; every unit increase in costs results in a τ_M unit increase in p^*_{ij}. Term (iv) is new, and is introduced because the general model allows for more than one insurer per market. It represents the change in hospital i's reimbursements from insurers $n \neq j$ when i is removed from j's network. 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 $\tilde{D}_n\tilde{\sigma}_{in} - D_n\sigma_{in} > 0$ and hence the higher are negotiated prices p^*_{ij}. Insurer competition may affect this term through several routes. First, if the presence of other competing MCOs allows consumers to switch plans in order to retain access to hospital i, this will have a positive effect on price. Second, as in term (ii), there is an indirect effect through other prices in the market. If insurer competition leads to an increase or decrease in hospital i's negotiated prices with MCO n, this will also affect i's prices with MCO j. Finally, as already noted, the entry of Kaiser in particular may have a negative effect on prices through this term. If consumers switch to Kaiser rather than to other MCOs when hospital i is dropped, they can no longer access i and this negative effect on term (iv) feeds through to a negative impact on price.

Without Insurer Competition. Note 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 (4) would be well approximated by:

$$p^*_{ij}\sigma_{ij} = \tau_H \left[\left(\phi_j - \tilde{\phi}_j \right) - \left(\sum_{h \in \mathcal{G}_j \setminus ij} p^*_{hj}(\sigma_{hj} - \tilde{\sigma}_{hj}) \right) \right] + \tau_M \left[\bar{c}_i \sigma_{ij} \right] + \epsilon_{ij}. \tag{6}$$

Thus, finding a relationship between prices and terms that are on the right-hand-side (RHS) of (4), but not (6), would suggest that employers and/or their enrollees were not captive to their MCOs, and, thus, insurer competition was 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 (4) in vector/matrix notation as:

$$\boldsymbol{p} \odot \boldsymbol{\sigma} = \tau_H [\underbrace{\boldsymbol{\phi}^{\Delta}}_{(i)} - \underbrace{\boldsymbol{\Sigma}^{\boldsymbol{\Delta}} \boldsymbol{p}}_{(iia)} - \underbrace{\boldsymbol{D}^{\boldsymbol{\Delta}} \odot (\boldsymbol{\Sigma} \boldsymbol{p})}_{(iib)}] + \tau_M [\underbrace{\boldsymbol{c} \odot \boldsymbol{\sigma}}_{(iii)} - \underbrace{\boldsymbol{\Sigma}^{\boldsymbol{D}}(\boldsymbol{p} - \boldsymbol{c})}_{(iv)}] + \boldsymbol{\epsilon} \tag{7}$$

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); $\boldsymbol{\phi}^{\boldsymbol{\Delta}}$ and $\boldsymbol{D}^{\boldsymbol{\Delta}}$

are $N \times 1$ vectors with:

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

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

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

The elements of (7), labelled $(i)-(iv)$, correspond to the elements of (4), where (ii) has been decomposed into two different parts, (iia) and (iib). Equation (7) will inform our estimation approach in the next section. Since negotiated prices enter both sides of (7), we will estimate this system of equations using instruments.

3 Empirical Application

We use the price equation in (7) 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 (7)). 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.[21]

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, Dranove and Satterthwaite (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.

[21] For example, we cannot 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.

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, derive the estimating equation based on (7) 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.[22] 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.

We use hospital characteristics, including location and costs, for hospitals from the American Hospital Association (AHA) survey.[23] 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.[24] Our final sample contains 233 hospital-insurer price observations (136 from BC, 97 from BS), comprising 149 unique hospitals.

[22] 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, Nevo and Town (2013).

[23] Our measure of costs is the average payroll cost 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).

[24] In robustness tests (reported later), we find our results are robust to the inclusion of all markets.

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. 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 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:

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

where $N_{k,m}$ is the commercially-insured population of market m in age-gender-zip code group k, γ^a_k 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 $\{\gamma^a_k\}_{\forall k}$ 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.[25] Probabilities $\{\gamma_{k,l}\}_{\forall k,l}$ are the realized probabilities for

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

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, Dranove and Satterthwaite (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:

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

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:

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

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.[26]

[26] 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

We note that the estimated demand model is valuable for this application for three reasons. First, as in Capps, Dranove and Satterthwaite (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

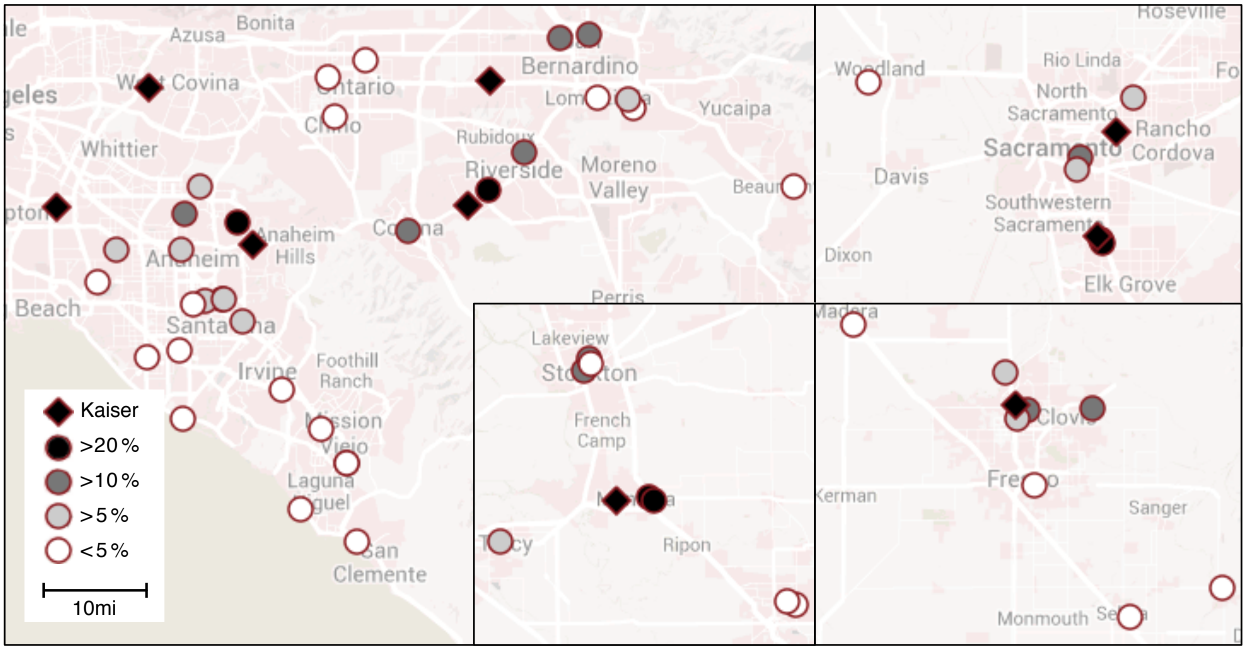
Our measure of insurer competition is intended to help capture the extent to which insurer j's demand, D_j, is affected by losing a given hospital i from its network. We use the proximity of consumers to a hospital owned by Kaiser Permanente. Kaiser is a vertically integrated MCO based in California. 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 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.[27] 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.

invariant to the potential selection of observable consumer types onto insurance plans.

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

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.

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

We use equations (4) and (7) from the bargaining model developed in the previous section as a basis for our main regression equation. As noted before, we can include certain terms from (7)—term (iia), representing the change in MCO j's payments to other hospitals, and term (iii), representing hospital costs—explicitly in our regression equation. We now discuss the variables used to proxy for the remaining terms.

We first discuss terms (i) and (iv). Term (i) is the reduction in insurer j's revenues per enrollee (coming from changes in both premium $(\phi_j(\mathcal{G}) - \phi_j(\mathcal{G} \setminus ij))$ and enrollment $(D_j(\mathcal{G}, \cdot) - D_j(\mathcal{G} \setminus ij, \cdot))$ when hospital i is dropped. In Appendix B, we provide a stylized example based on logit consumer demand for insurers and hospitals in which the attractiveness of a hospital (which we proxy for with ΔWTP_{ij}), the proximity to Kaiser, and an interaction between the two variables are shown to be suitable proxies for term (i).[28] Term (iv) represents the change in hospital i's payments from other insurers, per MCO j enrollee, when i and j come to a disagreement. Since hospital i's payments from other insurers are likely to change most substantially in cases where MCO j's change in revenues is also large (i.e., when many enrollees switch plans in response to hospital i being dropped from j's network), term (iv) will be highly related to term (i). We therefore use the same variables to proxy for both terms, and project terms (i) and (iv) onto: ΔWTP_{ij}, $Kaiser_i$, and an interaction between them.[29] Market fixed effects and demographic controls (discussed later) will also help control for these terms.

We now consider term (iib), $\sum_{h \in \mathcal{G}_j \setminus ij} p^*_{hj}((D_j - \tilde{D}_{j \setminus ij})\tilde{\sigma}_{hj})/D_j$, which represents the elements of the change in plan j's payments to other hospitals when i is dropped that are not captured by term (iia): that is, the reduced payments to other hospitals that come from j's enrollees switching to other plans when i is dropped. We take advantage of the fact that we can compute directly from hospital demand estimates the term $Pmt_{j,\setminus ij} \equiv \sum_{h \in \mathcal{G}_j \setminus ij} p^*_{hj} \hat{\tilde{\sigma}}_{hj \setminus ij}$, which is likely correlated with (iib). The part of (iib) not explicitly controlled for yet is the change in demand for j, per previous

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

[29] 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, Dranove and Satterthwaite (2003) and Gowrisankaran, Nevo and Town (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.

enrollee, when i is dropped. As with term (i), we use the ΔWTP_{ij} and $Kaiser_i$ variables to capture this demand effect. Thus, we capture the overall impact of term (iib) by using our constructed $Pmt_{j,\setminus ij}$ term, interacted with $Kaiser_i$ and $Kaiser_i \times \Delta WTP_{ij}$.[30]

Our final regression equation therefore becomes:

$$\begin{aligned}
\underbrace{P_{ij}}_{\hat{p}_{ij}\hat{\sigma}_{ij}} &= \alpha_1 \underbrace{\text{Cost}_{ij}}_{\bar{c}_i\hat{\sigma}_{ij}} + \alpha_2 \underbrace{\Delta Pmt_{j,\setminus ij}}_{\sum_{h\in\mathcal{G}_j\setminus ij}\hat{p}_{hj}(\hat{\sigma_{hj}}-\hat{\tilde{\sigma}}_{hj\setminus ij})} \\
&+\alpha_3 \Delta WTP_{ij} + \alpha_4 Kaiser_i + \alpha_5 Kaiser_i \times \Delta WTP_{ij} \\
&+ \underbrace{Pmt_{j,\setminus ij}}_{\sum_{h\in\mathcal{G}_j\setminus ij}\hat{p}_{hj}(\hat{\tilde{\sigma}}_{hj})} [\alpha_6 + \alpha_7 Kaiser_i + \alpha_8 Kaiser_i \times \Delta WTP_{ij}] \\
&+\boldsymbol{HSA}_m + BS_j + \boldsymbol{\beta} \times \boldsymbol{demogs}_i + \varepsilon_{ij}.
\end{aligned} \tag{8}$$

The first line represents the variables from (7) that can be directly controlled for. $P_{ij} \equiv \hat{p}_{ij}\hat{\sigma}_{ij}$ is the dependent variable in (7) and corresponds to the observed payment made to hospital i by MCO j per enrollee.[31] $\text{Cost}_{ij} \equiv \bar{c}_i\hat{\sigma}_{ij}$ is hospital i's average cost per MCO j enrollee and $\Delta Pmt_{j,\setminus ij}$ is the change in MCO j's payments per enrollee to other hospitals when hospital i is dropped from j's network. These are the three terms from equation (4) that can be included explicitly in the regression equation. 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 (7). 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 of (8) represent the variables (discussed previously) which are used to control for terms (i), (iia), and (iv) in (7). In addition, we include HSA fixed effects $\boldsymbol{HSA}_m$, an indicator that distinguishes between insurers BS_j, and demographic controls for the hospital's zip code, $\boldsymbol{demogs}_i$, as additional controls for these terms.[32] Note that our model indicates that these controls should influence the overall surplus generated by an MCO-hospital pair on a per-enrollee and not per-admission basis, further motivating the use of the price-per-enrollee as our dependent variable. We discuss the role of these control variables in the following section.

[30] We omit the other possible interaction term $Pmt_{j,\setminus ij} \times \Delta WTP_{ij}$ from 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.

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

[32] 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.

Interpreting the Regression Coefficients. We can use equation (4) to predict the signs of the regression equation coefficients. The model predicts that α_1 will be positive and α_2 negative: the negotiated price increases with hospital i's costs, while the change in MCO j's payments to other hospitals when i is dropped (a negative variable) has a negative sign in (4). The coefficient on ΔWTP_{ij} (α_3) absorbs the impact of hospital attractiveness on the insurer's outside option (through term (i) of equation (4)) and that of the hospital (through term (iv)). Since a more attractive hospital has a higher term (i) (the insurer loses more revenue by dropping it) and a more negative term (iv) (the hospital gains more revenue from other insurers when it is dropped), the model indicates that α_3 should be positive.

The sign on the $Kaiser_i$ coefficient (α_4) is theoretically ambiguous. It incorporates three effects of Kaiser competition on price. First, as already noted, with fixed premiums increased insurer competition is likely to increase term (i), implying a positive price effect. Second, when premiums are allowed to adjust, there may be an offsetting negative effect on this term due to a reduction in premiums and hence industry surplus. Third, term (iv) of the equation indicates that competition from Kaiser (as opposed to other insurers) may have a negative effect on price because enrollees who switch to Kaiser can no longer access hospital i; this reduces the hospital's outside option.

The coefficient on the interaction term between $Kaiser_i$ and ΔWTP_{ij} (α_5) captures the differential impact of Kaiser proximity on price for relatively attractive hospitals. There are reasons to suspect this term will be positive. For example, Kaiser may reduce the outside option of a very attractive hospital less than that of a typical provider because enrollees may prefer to switch to other non-Kaiser insurers in order to retain access to the "center of excellence". Alternatively, Kaiser might also reduce the outside option of the insurer more for more attractive hospitals, if there are more consumers whose utility falls enough to make them marginal between staying in insurer j and switching to Kaiser.

Finally, we can provide guidance for the signs of coefficients on the $Pmt_{j,\setminus ij}$ terms (α_6, α_7, and α_8). Recall that $Pmt_{j,\setminus ij}$ controls for the improvement in j's outside option due to consumers switching plans in response to a network change, thereby reducing j's payments to other hospitals. Consequently, we expect the coefficient on α_6 to be negative and, if increased exposure to Kaiser makes consumers more likely to switch insurers, the combined effect of $\alpha_7 + \alpha_8 \Delta WTP_{ij}$ should also be negative. If a larger number of marginal consumers switch to Kaiser when a very attractive hospital is dropped, we also expect α_8, the coefficient on the triple interaction term, to be negative.

3.6 Estimation and Identification

The econometric error in (8) $\varepsilon_{ij} \equiv \epsilon_{ij} + \nu_{ij}$ includes two sources of error. The first, ϵ_{ij}, is the MCO-hospital-specific cost shock defined in (5). 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 of these which are not controlled for by the observables on the last three lines of equation (8). 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 12 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, Ho and Varela (2013), employers' plan menus are often small. 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 (4). 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 (8) 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 (8) 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:

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

interacted with a constant, ΔWTP_{ij}, $Kaiser_i$, and $\Delta WTP_{ij} \times Kaiser_i$.[33] These excluded instruments, which comprise functions of costs and ΔWTP_{hj} of *other hospitals* ($h \neq i$) *in an insurer's network*, will be correlated with an insurer's payments to other hospitals.[34]

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}

[33] 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 $\boldsymbol{Z}$.

[34] 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 1: Summary Statistics

	Full	$\%_{0-25}$	$\%_{25-50}$	$\%_{50-75}$	$\%_{75-100}$
P_{ij} (per enrollee)	25.10	21.38	17.01	29.19	32.95
	(38.17)	(27.89)	(21.92)	(55.82)	(37.24)
ΔWTP_{ij}	0.109	0.0820	0.0823	0.145	0.129
	(0.208)	(0.0861)	(0.111)	(0.356)	(0.164)
$\Delta Pmt_{j\setminus ij}$	-25.03	-21.52	-19.22	-26.72	-32.76
	(34.03)	(27.32)	(23.07)	(45.42)	(35.38)
$Pmt_{j\setminus ij}$	348.2	340.0	390.1	311.0	350.9
	(97.17)	(73.36)	(150.4)	(52.40)	(63.00)
$Cost_{ij}$	20.77	15.54	14.21	24.30	29.13
	(26.80)	(17.22)	(16.69)	(36.40)	(29.35)
Blue Shield	0.416	0.397	0.407	0.414	0.448
	(0.494)	(0.493)	(0.495)	(0.497)	(0.502)
(3mi) $Kaiser_i$ (2004)	0.0534	0.000982	0.00470	0.0303	0.178
	(0.101)	(0.000758)	(0.00192)	(0.0192)	(0.141)
(3mi) $Kaiser_i$ (1995)	0.0423	0.000984	0.00459	0.0269	0.137
	(0.0794)	(0.000778)	(0.00213)	(0.0206)	(0.112)
Observations	233	58	59	58	58

mean coefficients; sd in parentheses

Notes: Means and standard deviations (in parenthesis) for variables used in price regressions, reported for the full sample and by quartile based on $(3mi)Kaiser_i$. N=233 hospital-insurer pairs. All price and cost terms (including $\Delta Pmt_{j\setminus ij}$ and $Pmt_{j\setminus ij}$) are rescaled to \$ per enrollee (accounting for probability of admission to hospital, conditional on age and gender).

in (5)), will be orthogonal to non-price variables on the RHS of (8) 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 (8)) 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

4.1 Summary Statistics and Data Variation

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 a particular

Table 2: Characteristics of Kaiser and Other Hospitals

	Kaiser Hospitals	Non-Kaiser Hospitals	Non-Kaiser $\%_{75-100}$
Number of beds	229.1 (119.0)	171.3 (125.8)	221.7 (142.6)
Nurses per bed	1.67 (0.78)	1.25 (0.53)	1.25 (0.62)
Physicians per bed	0.49 (0.63)	0.04 (0.09)	0.06 (0.15)
Offer CT scans	0.67 (0.49)	0.65 (0.48)	0.54 (0.51)
Offer PET scans	0.25 (0.45)	0.10 (0.30)	0.14 (0.35)
Have a NICU	0.42 (0.51)	0.29 (0.45)	0.32 (0.47)
Offer angioplasty	0.08 (0.29)	0.29 (0.45)	0.32 (0.47)
Offer oncology services	0.58 (0.51)	0.45 (0.50)	0.43 (0.50)

Notes: Means and standard deviations (in parenthesis) for characteristics of hospitals used in our price regressions and for Kaiser hospitals present in our data. N=149 for non-Kaiser hospitals, and N=12 for Kaiser hospitals. "Non-Kaiser $\%_{75-100}$" are the 37 hospitals in fourth quartile of $Kaiser_i$. Providers located in San Francisco, Oakland and Los Angeles HSAs are excluded. Characteristics taken from the American Hospital Association data 2003-4.

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.

The table also provides the mean and standard deviation of each variable by quartile of the $Kaiser_i$ distribution. There is some variation across quartiles (although the relationship is often not monotonic): for example hospitals located close to Kaiser are somewhat higher-quality, as measured by ΔWTP_{ij}, than other hospitals. Consistent with this, hospitals close to Kaiser have relatively high costs and high prices. These findings are not surprising given that Kaiser hospitals tend to be located in somewhat more urban areas than other hospitals. We note that most of the variation can be explained by differences in market characteristics: when we control for the market and demographic fixed effects that we include in our regression analysis, the residuals are not statistically different across quartiles of $Kaiser_i$. The purpose of the model is to analyze whether, conditional on hospital quality, cost, and our other controls, proximity to Kaiser has a separate (positive or negative) effect on price. We also note that the variation in every variable is at least as large within-quartile of $Kaiser_i$ as it is across quartiles. That is, even when we condition on $Kaiser_i$, substantial variation remains to identify the coefficients of interest in the regression equation.[35]

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 Kaiser hospitals and the others in our data. Kaiser hospitals are larger, with 229 beds on average, compared to 171 for other hospitals. They have somewhat more nurses per bed

[35]The three main inputs to the regression are positively correlated with each other but the correlations are fairly small. The correlation between ΔWTP_{ij} and the 2004 $Kaiser_i$ variable is 0.094, that between ΔWTP_{ij} and $Pmt_{j,\setminus ij}$ is 0.037 and that between $Kaiser_i$ and $Pmt_{j,\setminus ij}$ is 0.013.

and many more physicians per bed.[36] Their service provision is similar to that of other hospitals in many cases: for example, 67% of Kaiser hospitals and 65% of 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 25% and 10% respectively. Birthing services are also provided in substantially more Kaiser hospitals: 42% of Kaiser facilities in our data have a neonatal intensive care unit, for example, compared to 29% of other hospitals. There is no clear evidence in our data that Kaiser should be regarded as a poor substitute for other health insurers.

The third column of Table 2 summarizes the same characteristics for the 37 non-Kaiser hospitals with the greatest exposure to Kaiser (those in the top quartile of $Kaiser_i$). They have more beds and more physicians per bed than other non-Kaiser hospitals, consistent with their relatively high costs (Table 1). However, the other characteristics of the hospitals closest to Kaiser are not substantially different from the overall population, suggesting that the potential endogeneity issues discussed in the previous section are unlikely to be first-order concerns.

4.2 Estimation Results

Tables 3-4 contain our regression results. Standard errors are clustered by hospital.[37] Table 3 begins our build-up to the complete equation (8). 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); none of the coefficients change significantly relative to Model 1. The signs on all estimates are consistent with the predictions of our bargaining model laid out in (4).

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 (4): 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. First-stage regression results for the instruments used in this model are reported in the appendix.

[36] The number of physicians per bed is derived from the number of full-time-equivalent physicians, and the number of hospital beds, reported to the American Hospital Association in 2003. The number of FTE physicians is defined quite differently across US hospitals and also varies by physician contract structure. This may explain some of the large difference between the reported number of physicians per bed for Kaiser and for other hospitals. However, interviews with Kaiser executives also indicate that part of their strategy to maintain high-quality care is to employ a larger number of physicians per patient than the average across other hospitals.

[37] 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 (8). Dependent variable is expected price per enrollee paid by insurer j to hospital i. $\Delta \Pr ice$ 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. Table 4 reports our main results that add the terms proxying 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) to the specification. Its coefficient is negative, and is significant at p=0.05 when we use instruments. The negative sign indicates that, on average, competition from Kaiser has a negative effect on negotiated prices. We then add variables to the regression to allow for heterogeneous effects across hospitals.

In Model 5 we add a term interacting ΔWTP_{ij} with $Kaiser_i$. The $Kaiser_i$ coefficient remains negative and significant; that on the interaction is positive but insignificant in both OLS and IV specifications. This is suggestive evidence that more attractive hospitals are less negatively affected by insurer competition than other providers. The final two specifications investigate this further by adding the variables that proxy for the impact of Kaiser on term (iib) in equation (4): interactions of $Pmt_{j,\setminus ij}$ with $Kaiser_i$ and ΔWTP_{ij}. If our model is correct, we expect a negative overall effect of Kaiser on term (iib), since insurer competition improves plan j's outside option by reducing enrollment (and therefore its payments to other hospitals) when i is dropped. Further, the argument made earlier—that this effect may be stronger for more attractive hospitals—implies a negative coefficient on the triple interaction term.

Almost all of the estimates are consistent with this reasoning. Model 6 in the table adds the triple interaction term; its coefficient is negative and significant as expected. Model 7 is the full specification: it also adds the double interaction between $Kaiser_i$ and $Pmt_{j,\setminus ij}$. This specification

Table 4: Price Regressions Including Measure of Insurer Competition

	(1) Model 4	(2) Model 4 IV	(3) Model 5	(4) Model 5 IV	(5) Model 6	(6) Model 6 IV	(7) Model 7	(8) Model 7 IV
ΔWTP_{ij}	52.08^{***}	52.12^{***}	52.38^{***}	53.04^{***}	46.88^{**}	50.22^{***}	45.74^{**}	49.84^{***}
	(18.15)	(4.672)	(19.08)	(5.249)	(18.96)	(5.662)	(18.47)	(6.231)
$Cost_{ij}$	0.723^{***}	0.289^{***}	0.706^{**}	0.294^{***}	0.720^{**}	0.292^{***}	0.733^{**}	0.328^{***}
	(0.280)	(0.0717)	(0.282)	(0.0766)	(0.283)	(0.101)	(0.286)	(0.0980)
$\Delta Pmt_{j\setminus ij}$	-0.167	-0.504^{***}	-0.166	-0.485^{***}	-0.199	-0.498^{***}	-0.196	-0.463^{***}
	(0.320)	(0.0637)	(0.323)	(0.0631)	(0.320)	(0.0747)	(0.317)	(0.0759)
$Pmt_{j\setminus ij}$	-0.0596^{***}	0.0000928	-0.0579^{***}	0.000687	-0.0461^{**}	0.00505	-0.0486^{**}	-0.00596
	(0.0209)	(0.0175)	(0.0210)	(0.0172)	(0.0197)	(0.0174)	(0.0201)	(0.0190)
(3mi) $Kaiser_i$	-10.02	-8.231^{**}	-15.66^{**}	-10.11^{*}	-12.30^{*}	-9.959^{*}	-157.8^{*}	-299.5^{***}
	(9.546)	(4.016)	(7.738)	(5.727)	(6.906)	(5.322)	(90.43)	(78.24)
(3mi) $Kaiser_i * \Delta WTP_{ij}$			41.53	27.44	690.0^{***}	690.6^{***}	1017.5^{***}	1330.7^{***}
			(83.53)	(31.81)	(134.0)	(53.26)	(215.4)	(195.5)
(3mi) $Kaiser_i * \Delta WTP_{ij} * Pmt_{j\setminus ij}$					-1.905^{***}	-1.801^{***}	-2.815^{***}	-3.556^{***}
					(0.430)	(0.156)	(0.624)	(0.537)
(3mi) $Kaiser_i * Pmt_{j\setminus ij}$							0.410	0.816^{***}
							(0.254)	(0.225)
Observations	233	233	233	233	233	233	233	233

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

Notes: Results for regression equation (8). Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

includes all the terms required to control for the different mechanisms by which insurer competition, and hospital quality, can affect the negotiated price in the bargaining model, and this cleans up the estimates considerably. The coefficient on $Kaiser_i$ remains negative and is significant at p=0.01; the $Kaiser_i$ * ΔWTP_{ij} interaction is now positive and significant and the $Pmt_{j,\setminus ij}$ coefficient is negative (although not significant when we use instruments). The implied average effect of $Kaiser_i$ on term (iib) does not always have the predicted negative sign, but it is not significantly positive for most hospitals. The triple interaction coefficient is negative and significant at p=0.01, consistent with the argument made above.

Magnitudes. The estimates indicate that the trade-offs between the different mechanisms by which Kaiser can affect prices differ across hospitals, implying a different Kaiser effect for very attractive hospitals compared to other providers. We now calculate the implied overall price effect for different types of hospitals.

We consider first the impact for the majority of hospitals. For hospitals above the 25th percentile of ΔWTP_{ij}, the estimated impact of the variables proxying for terms (i) and (iv) of equation (4) ($Kaiser_i$ and its interaction with ΔWTP_{ij}) is negative, suggesting that Kaiser competition leads to premium competition and a reduction in the hospital's outside option and these negative effects outweigh the benefits. Overall, for these hospitals, the predicted impact of increasing the share of patients who have access to a Kaiser hospital within 3 miles of their zip code by one standard deviation (.10) is an average price reduction of \$400 (compared to a mean price of \$5978 in our sample). For hospitals above the 50th percentile of ΔWTP_{ij} the effect of the $Kaiser_i$ and $Kaiser_i$ * ΔWTP_{ij} terms is less negative, suggesting that Kaiser's impact on the insurer's outside option, which tends to increase prices, is larger. Overall the corresponding effect is a price reduction of \$125 per patient.

Now consider the most attractive hospitals in the sample. For providers above the 75th percentile of ΔWTP_{ij}, the predicted effect of the $Kaiser_i$ and $Kaiser_i$ * ΔWTP_{ij} terms becomes positive, generating a positive overall effect of proximity to Kaiser on prices. Increasing the share of patients within 3 miles of a Kaiser hospital is predicted to lead to an average price increase of \$31 per admission for these hospitals. The estimates are consistent with our suggested story: that for very attractive hospitals, Kaiser competition harms the insurer's outside option much more than that of the hospital, and this dominates the mechanisms through which prices may be reduced. The effect is more pronounced for even higher-quality hospitals: the predicted effect of increased proximity to Kaiser is a price increase of \$120 for hospitals above the 90th percentile of ΔWTP_{ij} and to \$299 for hospitals above the 95th percentile.

Finally we note that, as discussed earlier, the coefficients on $Cost_{ij}$ and $\Delta Pmt_{j,\setminus ij}$. correspond to the bargaining weights $\{\tau_M, -\tau_H\}$ of MCOs and hospitals from our bargaining model in (4). These coefficients are statistically significant. The sum of their absolute values equaling 1 cannot be statistically rejected, which is consistent with our model.

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)	(8.287)
$Cost_{ij}$	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)	(78.24)	(53.93)	(32.23)	(21.84)	(12.68)
$Kaiser_i * \Delta WTP_{ij}$	1477.4***	1330.7***	914.4***	481.3***	317.1***	153.0***
	(513.8)	(195.5)	(189.5)	(159.1)	(99.95)	(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)
$Kaiser_i * Pmt_{j\setminus ij}$	0.702*	0.816***	0.552***	0.298***	0.207***	0.119***
	(0.404)	(0.225)	(0.157)	(0.0942)	(0.0652)	(0.0387)
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 (8), 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.

4.3 Robustness

We now discuss the results of several robustness tests.

Alternative Distances. Table 5 reports results from using our full model specification (Model 7 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 $3mi$ in Table 5 corresponds to column (8) 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

Table 6: Price Regressions with Drive Times

	(1) 10 mins	(2) 15 mins	(3) 20 mins	(4) 25 mins	(5) 30 mins	(6) 35 mins
ΔWTP_{ij}	44.39***	42.39***	33.93***	15.31	17.98	15.08
	(6.871)	(7.119)	(10.65)	(16.66)	(16.21)	(14.91)
$Cost_{ij}$	0.395***	0.291***	0.290***	0.399***	0.362***	0.364***
	(0.111)	(0.107)	(0.0975)	(0.0993)	(0.106)	(0.111)
$\Delta Pmt_{j\setminus ij}$	-0.493***	-0.554***	-0.601***	-0.595***	-0.611***	-0.606***
	(0.0835)	(0.0818)	(0.0696)	(0.0688)	(0.0697)	(0.0684)
$Pmt_{j\setminus ij}$	-0.00484	-0.0183	-0.0435**	-0.0464**	-0.0251	-0.0137
	(0.0179)	(0.0181)	(0.0199)	(0.0216)	(0.0215)	(0.0222)
$Kaiser_i$	-154.7**	-86.17***	-46.09***	-27.12**	-11.93	-8.881
	(71.07)	(27.19)	(14.90)	(13.17)	(12.78)	(13.25)
$Kaiser_i * \Delta WTP_{ij}$	474.7**	321.8***	185.3***	202.8***	163.7***	157.6***
	(234.3)	(119.1)	(45.43)	(35.81)	(35.63)	(36.16)
$Kaiser_i * \Delta WTP_{ij} * Pmt_{j\setminus ij}$	-1.553***	-0.925***	-0.554***	-0.600***	-0.480***	-0.447***
	(0.599)	(0.286)	(0.116)	(0.107)	(0.103)	(0.106)
$Kaiser_i * Pmt_{j\setminus ij}$	0.423**	0.243***	0.123***	0.0643	0.0212	0.0124
	(0.203)	(0.0826)	(0.0469)	(0.0432)	(0.0408)	(0.0419)
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 (8), 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.

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.[38] We consider drive times between 10 minutes and 30 minutes. The results in every specification are comparable to the main specification: the Kaiser coefficient is again negative and significant, its interaction with ΔWTP_{ij} positive and significant, and the triple interaction negative and significant.[39] 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}.

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

[39] 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) BS only	(4) Systems
ΔWTP_{ij}	48.61***	49.98***	104.9***	22.26**
	(7.170)	(5.971)	(9.631)	(10.82)
$Cost_{ij}$	0.266***	0.292***	0.330***	1.284***
	(0.0580)	(0.0988)	(0.116)	(0.0545)
$\Delta Pmt_{j\setminus ij}$	-0.515***	-0.493***	-0.322***	.0839*
	(0.0573)	(0.0771)	(0.0748)	(0.0472)
$Pmt_{j\setminus ij}$	0.00171	0.000901	0.00372	0.0785
	(0.0166)	(0.0186)	(0.0106)	(0.0270)
(3mi) $Kaiser_i$	-103.4*	-155.4**	-348.0***	-108.6
	(56.35)	(72.87)	(85.77)	(68.20)
(3mi) $Kaiser_i * \Delta WTP_{ij}$	713.9***	1018.5***	1777.4***	264.7***
	(174.9)	(182.6)	(183.2)	(81.78)
(3mi) $Kaiser_i * \Delta WTP_{ij} * Pmt_{j\setminus ij}$	-1.561***	-2.697***	-5.017***	–0.760***
	(0.417)	(0.511)	(0.485)	(0.232)
(3mi) $Kaiser_i * Pmt_{j\setminus ij}$	0.274*	0.409*	0.933***	0.276
	(0.159)	(0.211)	(0.231)	(0.200)
$\sum_{h\in\mathcal{S}_i\setminus i} P_{hj}$				-0.0205*
				(0.0121)
$\sum_{h\in\mathcal{S}_i\setminus i} Cost_{hj}$				0.109***
				(0.0307)
Observations	341	233	97	233

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

Notes: Columns (1)-(2) report GMM results for regression equation (8), and Column (3) reports GMM results for regression equation (13) (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) only includes observations involving BlueShield. Column (4) 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.

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 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.[40] 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}.

As noted in Section 3.6 one possible selection concern is that, if Kaiser selects enrollees based on price sensitivity, this implies an impact on the optimal prices of nearby firms. In particular, if insurers pass some proportion of hospital prices through to patients using co-insurance rates, this could impact the prices negotiated with hospitals located close to Kaiser and therefore affect the interpretation of our results. We note that, while Blue Cross uses co-insurance rates for patients in our data, Blue Shield uses only co-pays that are fixed across hospitals. As a robustness test we therefore repeat the analysis using Blue Shield observations only. Column (3) of Table 7 presents the results. All coefficients of interest have the same sign as our main specification, and are again significant, although some of the magnitudes (particularly those on ΔWTP_{ij} and the triple interaction term) are larger in this specification.

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 C.2 of the Appendix, we discuss how the model in Section 2 can be modified to allow for hospital systems

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

jointly negotiating with insurers, and we derive a regression equation similar to (8). 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 (4) of Table 7. Adding the impact of negotiating as a system still yields significant coefficients with the same signs on ΔWTP_{ij} and $Kaiser_i \times \Delta WTP_{ij}$; $Kaiser_i$, still negative, is not statistically significant (though similar magnitude to specifications (1)-(2)). Coefficients on all terms including ΔWTP_{ij} are smaller due to the fact that systems yield higher values of ΔWTP_{ij} than if hospitals negotiated on their own. The estimates imply that the average effect of increasing proximity to Kaiser by 10% is a price reduction of \$600 for hospital systems above the 50th percentile of ΔWTP_{ij}, and a price increase of \$95 for those above the 95th percentile of ΔWTP_{ij}.

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}).

Unfortunately, we do not have sufficient data to estimate a full model of insurer competition, and we believe this would be needed to identify which exact mechanisms are responsible for these heterogeneous effects. However, since our regressions include variables that separately account for some of the mechanisms by which Kaiser affects the bargaining outcome, we are able to at least shed some light on this issue. For most hospitals, the impact of Kaiser competition on premiums—shrinking the surplus to be divided between insurer and hospitals—together with its negative effect on the hospital's outside option generate a negative overall price effect. However, for the most attractive hospitals, it seems that Kaiser's impact on the insurer's loss in enrollment when the hospital is dropped outweighs these negative effects.

We provide here one story that could explain this finding for attractive hospitals. If the insurer drops a center of excellence in a market where it does not compete with Kaiser, many enrollees may switch to other plans in order to retain access to the hospital. If Kaiser is added to the market, this may have little effect on the behavior of those switchers, implying little impact on the hospital's outside option. However it may induce other enrollees, who were previously on the margin between remaining with the original insurer and moving away, to switch to Kaiser. Our estimates are consistent with this story.[41] It implies that Kaiser damages the outside option of the

[41] For example the negative triple interaction term is consistent with more enrollees switching away from the insurer, in the presence of competition from Kaiser, when a more attractive hospital is dropped.

insurer but not that of the center of excellence, generating a positive price effect of Kaiser for these hospitals.[42]

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 (4). 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, including a potential 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 together with the effect on the hospital's threat point outweighs other effects and consequently depresses negotiated input prices.

Finally, although our theoretical analysis of the impact of insurer competition on negotiated prices is fairly general, we acknowledge that the magnitudes of our empirical findings may be particular to Kaiser. First (as noted earlier), since a consumer switching to Kaiser cannot access non-Kaiser hospitals, Kaiser also adversely affects a hospital's outside option when bargaining with other insurers. Second, since Kaiser is vertically integrated, increased insurer competition due to Kaiser's presence necessarily adds Kaiser hospitals and physicians to a market. Though we stress that insurer competition must be relevant if the presence of Kaiser hospitals or doctors influences the negotiated prices between non-Kaiser hospitals and insurers (because Kaiser's presence should have no effect on prices if consumers and employers do not substitute across insurers), it is difficult for us to extrapolate the magnitude of the price effect if a non-integrated insurer were to enter a market. In particular, entry by a non-integrated insurer could lead to recontracting among existing hospitals by both the new and existing insurers in addition to the effects analyzed in this paper. The impact of the increased insurer competition on negotiated prices would be likely to vary with the contracting outcome.[43] An analysis of this type of non-integrated entry would require a model

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

[43] For example, consider a new insurer entering a market against an incumbent insurer. Two potential outcomes include: (i) the entrant and incumbent contracting with all hospitals; or (ii) the entrant and incumbent "splitting" the market and selectively contracting with disjoint sets of hospitals. The change in negotiated prices will depend on, among other things, which contracting outcome is realized.

of renegotiation and network formation which is outside the scope of this paper (but the subject of ongoing research; see, e.g., Lee and Fong (2013)). Nonetheless, the tools and results presented here provide important insights to better understand how increased competition in the insurer market affects negotiated outcomes.

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.

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A Hospital 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. As in Ho (2006), we implicitly assume there is no selection across our two insurance plans on unobservable consumer preferences for hospitals.

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 Regression Analysis: Further Details

B.1 First Stage Results for Instruments

Table 11 reports first-stage regression results for the instruments used in Model 3 IV reported in Table 3.

B.2 Motivation for Regressors

Our use of ΔWTP_{ij} and $Kaiser_i$ to control for terms in (4) can be motivated by considering the following stylized example. Assume there are two insurers j and k in a market, and a consumer's utility for each insurer $l \in \{0, j, k\}$ (where 0 represents the outside good) is given by $u_l = \delta_l + \epsilon_l$, where ϵ is distributed Type I extreme value, and let $\delta_0 = 0$. Let $\tilde{u}_j = \delta_j - \alpha \Delta WTP_{ij} + \epsilon_j$ denote the utility derived for a consumer from insurer j's plan if j and hospital i come to a disagreement, which is consistent with a consumer's utility from an insurer being a function of the expected option value of accessing that insurer's network (c.f. Capps, Dranove and Satterthwaite (2003)). For exposition, normalize $\alpha = 1$.

Based on this setup, we can derive the "logit" shares of consumers who visit insurer j as:

$$D_j = \frac{\exp(\delta_j)}{1 + \exp(\delta_j) + \exp(\delta_k)} \qquad \tilde{D}_j = \frac{\exp(\delta_j - \Delta WTP_{ij})}{1 + \exp(\delta_j - \Delta WTP_{ij}) + \exp(\delta_k)}$$

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.

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

Table 11: First-Stage Results for Instruments

	$\Delta Pmt_{j\setminus ij}$	$Pmt_{j\setminus ij}$
$\sum_{h\in\mathcal{G}_j\setminus ij}\Delta WTP_{hj}(\hat{\sigma}_{hj}-\hat{\tilde{\sigma}}_{hj})$	5448.5***	-14719.2***
	(752.6)	(3790.5)
$\sum_{h\in\mathcal{G}_j\setminus ij}\bar{c}_h^1(\hat{\sigma}_{hj}-\hat{\tilde{\sigma}}_{hj})$	0.166	5.206
	(0.660)	(3.323)
$\sum_{h\in\mathcal{G}_j\setminus ij}\bar{c}_h^2(\hat{\sigma}_{hj}-\hat{\tilde{\sigma}}_{hj})$	0.0902	-1.048
	(0.258)	(1.300)
$\sum_{h\in\mathcal{G}_j\setminus ij}\Delta WTP_{hj}(\hat{\tilde{\sigma}}_{hj})$	211.6***	220.2
	(78.68)	(396.3)
$\sum_{h\in\mathcal{G}_j\setminus ij}\bar{c}_h^1(\hat{\tilde{\sigma}}_{hj})$	0.118	1.546**
	(0.130)	(0.656)
$\sum_{h\in\mathcal{G}_j\setminus ij}\bar{c}_h^2(\hat{\tilde{\sigma}}_{hj})$	-0.0150	-0.212
	(0.0488)	(0.246)
Observations	233	233
Adjusted R^2	0.479	0.205
Fstat	37.23	11.49

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

Notes: First stage OLS regressions for dependent variables in (8), controlling for ΔWTP_{ij}, costs, market and insurer fixed effects, and demographic controls. $\bar{c}_h^1$ and $\bar{c}_h^2$ represent hospital h's payroll and expenses per admission.

Combining these equations, we derive the following:

$$\Delta^{\%}D_{j,i} \equiv \frac{D_j - \tilde{D}_j}{D_j} = 1 - \exp(-\Delta WTP_{ij})\frac{1+\exp(\delta_j)+\exp(\delta_k)}{1+\exp(\delta_j - \Delta WTP_{ij})+\exp(\delta_k)} \tag{9}$$

where the LHS of (9) corresponds to inputs into terms (i) and (iib) of (4). This equation motivates our use of ΔWTP_{ij} and $Kaiser_i$ in our regression equation, as $Kaiser_i$ controls the relative attractiveness of Kaiser (δ_k) to a consumer. Note that $\partial(\Delta^{\%}D_{j,i})/\partial(\Delta WTP_{ij}) > 0$ and $\partial(\Delta^{\%}D_{j,i})/\partial(\delta_k) > 0$: i.e., increases in the attractiveness of Kaiser and hospital i to an insurer's network leads to greater percentage changes in insurer j's demand upon losing hospital i. Furthermore, note that this effect is reinforcing, as $\partial^2(\Delta^{\%}D_{j,i})/\partial(\Delta WTP_{ij})\partial(\delta_k) > 0$: i.e., the impact of an losing a more attractive hospital on the percentage change in insurer j's demand is increasing as Kaiser becomes a more viable alternative for consumers.[44]

[44] We follow the literature in constructing ΔWTP_{ij} as a weighted average across consumer characteristics and diagnoses (Town and Vistnes (2001), Capps, Dranove and Satterthwaite (2003)). Ideally, we would integrate over the predicted change in demand across individuals, but this is infeasible given our current approach which does not estimate insurance demand.

Table 12: 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.

B.3 List of Kaiser Hospitals

Table 12 lists the names and brief histories of the 27 Kaiser hospitals active in California in 2004 that are used in our analysis.

C Additional Robustness Tests

C.1 Price-Per-Admission Regressions

Motivated by the unscaled FOC from our bargaining model in terms of price-per-admission:

$$\begin{aligned} p_{ij}^* =&\tau_H \left[\frac{D_j \phi_j - \tilde{D}_{j\setminus ij} \tilde{\phi}_{j\setminus ij}}{D_j \sigma_{ij}} - \left(\frac{\sum_{h \in \mathcal{G}_j \setminus ij} p_{hj}^* (\sigma_{hj} - \frac{\tilde{D}_{j\setminus ij}}{D_j} \tilde{\sigma}_{hj\setminus ij})}{\sigma_{ij}} \right) \right] \\ &+ \tau_M \left[\bar{c}_i - \frac{\sum_{n \in \mathcal{G}_i \setminus ij} (D_n \sigma_{in} - \tilde{D}_{n\setminus ij} \tilde{\sigma}_{in\setminus ij})(p_{in}^* - \bar{c}_i)}{D_j \sigma_{ij}} \right] + \frac{\epsilon_{ij}}{\sigma_{ij}}. \end{aligned} \tag{10}$$

(which is simply a rescaling of (4)), we estimate a variant of our regression equation given by (8) but scaling both sides by σ_{ij}, the share of enrollees on each insurer j who visit each hospital j. This equation thus regresses price-per-admission for each hospital-insurer pair onto the same set of (scaled) variables. Results are provided in Table 13, and estimates are broadly similar to those provided in the main text.

C.2 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:

$$\begin{aligned} p_{ij} \in \arg\max & \left[\pi_{j,\mathcal{M}}(\boldsymbol{p}, \mathcal{G}) - \pi_{j,\mathcal{M}}(\boldsymbol{p}_{-sj}, \mathcal{G} \setminus \{hj\}_{h \in \mathcal{S}_s})\right]^{\tau_M} \\ & \times \left[\pi_{s,\mathcal{S}}(\boldsymbol{p}, \mathcal{G}) - \pi_{s,\mathcal{S}}(\boldsymbol{p}_{-sj}, \mathcal{G} \setminus \{hj\}_{h \in \mathcal{S}_s})\right]^{\tau_H} \;\; \forall ij \in \mathcal{G}, i \in \mathcal{S}_s \end{aligned} \tag{11}$$

This is the corresponding bargain as (11), 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 13: Price-Per-Admission Regressions with Alternative Distances

	(1) 2 mi	(2) 3 mi	(3) 4 mi	(4) 5 mi	(5) 7 mi	(6) 10 mi
ΔWTP_{ij}	56.00***	61.34***	57.77***	56.24***	52.89***	54.45***
	(9.596)	(9.176)	(7.763)	(6.889)	(5.533)	(7.030)
$Cost_{ij}$	0.383***	0.406***	0.397***	0.388***	0.398***	0.407***
	(0.0643)	(0.0634)	(0.0616)	(0.0614)	(0.0623)	(0.0643)
$\Delta Pmt_{j\setminus ij}$	-0.435***	-0.400***	-0.564***	-0.542***	-0.503***	-0.502***
	(0.0891)	(0.0828)	(0.0924)	(0.0869)	(0.109)	(0.123)
$Pmt_{j\setminus ij}$	0.00725	0.0141**	0.0138**	0.0101	0.00944	0.00829
	(0.00587)	(0.00588)	(0.00607)	(0.00630)	(0.00610)	(0.00594)
$Kaiser_i$	-60.78***	-13.89	-17.26**	-20.51***	-13.10***	-8.343**
	(19.40)	(13.18)	(7.715)	(4.447)	(3.790)	(3.350)
$Kaiser_i * \Delta WTP_{ij}$	712.7***	663.2***	706.5***	491.3***	254.4***	135.1**
	(173.7)	(49.69)	(53.04)	(47.87)	(59.79)	(56.81)
$Kaiser_i * \Delta WTP_{ij} * Pmt_{j\setminus ij}$	-2.063***	-1.649***	-1.795***	-1.250***	-0.654***	-0.362**
	(0.487)	(0.169)	(0.184)	(0.122)	(0.157)	(0.156)
$Kaiser_i * Pmt_{j\setminus ij}$	0.163***	0.0266	0.0429*	0.0557***	0.0347***	0.0216*
	(0.0566)	(0.0396)	(0.0256)	(0.0140)	(0.0126)	(0.0117)
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 (8) where all LHS and RHS terms are scaled by σ_{ij}. All price terms are instrumented, and $Kaiser_i$ is the share of hospital i's patients who live within x miles of a Kaiser hospital (with distances varying based on the column). Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

as hospital i. Then for each hospital $i \in \mathcal{S}_i$, the FOC of (11) can be expressed as:

$$\underbrace{p^*_{ij}\sigma_{ij}}_{\text{hospital price / enrollee}} = \tau_H \left[\underbrace{\left(\frac{D_j\phi_j - \tilde{D}_j\tilde{\phi}_j}{D_j} \right)}_{\text{(i) } \Delta \text{ MCO revenues}} - \underbrace{\left(\sum_{h \in \mathcal{G}_j \setminus \{lj\}_{l \in \mathcal{S}_i}} p^*_{hj}(\sigma_{hj} - \tilde{\sigma}_{hj} + \frac{D_j - \tilde{D}_j}{D_j}\tilde{\sigma}_{hj}) \right)}_{\text{(ii) } \Delta \text{ MCO } j \text{ payments to other hospitals not in } \mathcal{S}_i} \right] \tag{12}$$

$$+ \tau_M \left[\underbrace{\bar{c}_i\sigma_{ij}}_{\text{(iii) hospital costs / enrollee}} - \underbrace{\sum_{n \in \mathcal{G}_i \setminus ij} \sum_{h \in \mathcal{S}_i} \frac{(D_n\sigma_{hn} - \tilde{D}_n\tilde{\sigma}_{hn})}{D_j}(p^*_{hn} - \bar{c}_h)}_{\text{(iv) } \Delta \text{ System } \mathcal{S}_i \text{ profits from other MCOs}} \right]$$

$$- \underbrace{\sum_{h \in \mathcal{S}_i \setminus i} \sigma_{hj}\left[p_{hj} - \tau_M\bar{c}_h\right]}_{\text{(v) Loss in profits of other system hospitals from MCO } j} + \epsilon_{ij}$$

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 (4), if there were no hospital systems (or hospitals bargained independently).

Estimation. Informed by the FOCs given by (12), we modify our estimation equation (8) to account for systems as follows:

$$\begin{aligned}
\underbrace{P_{ij}}_{\hat{p}_{ij}\hat{\sigma}_{ij}} = \; & \alpha_1 \underbrace{\text{Cost}_{ij}}_{\bar{c}_i\hat{\sigma}_{ij}} + \alpha_2 \underbrace{\Delta Pmt_{j,\setminus \mathcal{S}_i j}}_{\sum_{h \in \mathcal{G}_j \setminus \{lj\}_{l \in \mathcal{S}_i}} \hat{p}_{hj}(\hat{\sigma_{hj}} - \hat{\tilde{\sigma}}_{hj})} \\
& + \alpha_3 \Delta WTP_{\mathcal{S}_i j} + \alpha_4 Kaiser_i + \alpha_5 Kaiser_i \times \Delta WTP_{\mathcal{S}_i j} \\
& + \underbrace{Pmt_{j,\setminus \mathcal{S}_i j}}_{\sum_{h \in \mathcal{G}_j \setminus \{lj\}_{l \in \mathcal{S}_i}} \hat{p}_{hj}(\hat{\tilde{\sigma}}_{hj})} [\alpha_6 + \alpha_7 Kaiser_i + \alpha_8 Kaiser_i \times \Delta WTP_{\mathcal{S}_i j}] \\
& + \alpha_9 \sum_{h \in \mathcal{S}_i \setminus i} P_{hj} + \alpha_{10} \sum_{h \in \mathcal{S}_i \setminus i} Cost_{hj} \\
& + \boldsymbol{HSA}_m + BS_j + \boldsymbol{\beta} \times \boldsymbol{demogs}_i + \varepsilon_{ij}.
\end{aligned} \tag{13}$$

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 (12).

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