Insurer Competition and Negotiated Hospital Prices

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PRELIMINARY AND INCOMPLETE

Abstract

We examine the impact of increased health insurer competition on negotiated hospital prices. Insurer competition can lead to lower premiums holding fixed hospital prices; however, hospitals may also leverage each insurer's weaker outside option when bargaining to negotiate higher prices. We use a theoretical bargaining model to derive a regression equation where price is expressed in terms of changes in the following variables when a hospital is dropped from an 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. We estimate a model of consumer demand for hospitals and use it to derive many of the independent variables specified in the regression equation, and use the presence of Kaiser Permanente in the hospital's market to proxy for the level of insurer competition. Leveraging a unique dataset on negotiated prices between hospitals and commercial insurers in California in 2004, we find that increased insurer competition has a positive and empirically meaningful effect on the prices of high utility generating hospitals. This effect is relevant for policymakers as it can offset anticipated premium reductions, and has not been emphasized in the recent literature on hospital-insurer bargaining.

1 Introduction

Competition between health insurers has been a focus of policy-makers in recent years. One of the main objectives of the Health Insurance Exchanges (HIXs) to be established under the Patient Protection and Affordable Care Act of 2010 is to facilitate insurer competition, with the goal of generating reduced premiums to employers and consumers and increased coverage and quality of care.[1] Though there is evidence that increased insurer competition may lead to lower premiums (Dafny (2010), Dafny et al. (2012)), the fact that the input market for health services is imperfectly competitive and health providers such as hospitals and physician groups negotiate with insurers

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[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.

means the impact of competition on negotiated input prices is ambiguous. Increased insurer competition may reduce premiums charged to employers and enrollees and therefore place a downward pressure on provider prices as there is less surplus to be split among the bargaining parties. However, the ability of consumers to more easily switch insurance plans if a particularly attractive hospital is dropped reduces the insurer's outside option from disagreement, allowing hospitals to "play" insurers off one another and giving them greater leverage to negotiate higher rates. Previous papers have found evidence, consistent with this, that average hospital prices can rise in response to increased insurer competition (Moriya et al. (2010), Melnick et al. (2010)). This positive price effect, which offsets some of the benefits of insurer competition, is a variant of the countervailing power hypothesis that concentration downstream can lead to lower negotiated input prices from upstream firms (Galbraith (1952)).

This effect is likely to become more important as provider consolidation increases, not only within physician groups or hospitals but also across them (e.g., with the establishment of Accountable Care Organizations (ACOs) allowed for under the recent health reforms). Higher negotiated rates can directly affect consumer surplus if they lead to higher premiums. Even if premiums do not increase, increased 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 that could have substantial welfare effects.

This paper's primary objective is to investigate the existence and magnitude of the impact of insurer competition on negotiated hospital prices. In our study, we emphasize the potential heterogeneous impact of such competition across different hospitals, an important feature which to our knowledge has not been studied in the previous literature. We leverage a unique admission and claims dataset provided by a public agency with over 1M covered lives which contains negotiated prices paid by two of the largest commercial insurers in California to hospitals in 2004, and also use information on the precise hospital networks provided by these two insurers.

Most recent papers on insurer-hospital bargaining consider other potentially important aspects of the bargaining process but abstract away from issues of insurer competition, primarily in response to data limitations and modeling complexities (e.g., Capps et al. (2003), Gowrisankaran et al. (2013), and Lewis and Pflum (2013)).[2] Recent papers finding evidence of large enrollee switching costs of moving between plans (e.g. Handel (forthcoming)) and demonstrating that employers offer quite restricted menus of plans to their employees (Dafny et al. (2013)) suggest the presence of frictions that could prevent enrollees from moving in response to network changes; this might imply a small bargaining effect. However, we show that the effect of insurer competition on negotiated prices can be substantial. We argue that policy decisions regarding the need to emphasize competition between health insurers should take the impact on input prices into account.

To conduct our empirical exercise, we use a theoretical model of bargaining between an insurer and hospital to inform a regression equation relating the negotiated price to changes in the following

[2]Ho (2006, 2009) and Lee and Fong (2012) are exceptions. However, none of these papers empirically estimate the magnitude of the effect of insurer competition on input prices.

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 the regressors control for the outside options of each hospital and insurer, and will require predicting utilization patterns if a hospital is dropped from a given insurer's network; we do so 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. The dependent variables that cannot be directly predicted using our hospital demand model comprise changes in the insurer's demand and premiums, and changes in the hospital's payments from other insurers, when a given hospital is dropped from an insurer's network. The basis of our approach is to proxy for these variables with measures of (i) the degree of insurer competition within that hospital's local market, and (ii) the willingness-to-pay of consumers for access to this hospital on an insurer's network.

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, many of which were established more than a decade before the time period in question. Kaiser is the largest insurer in California (and largest managed care organization (MCO) in the US), with a HMO enrollee market share of approximately 40%. Kaiser is vertically integrated; it owns a network of providers and rarely refers patients to hospitals outside its network. Since non-Kaiser enrollees do not access Kaiser hospitals, and Kaiser enrollees do not access non-Kaiser hospitals, Kaiser affects the bargaining process between a non-Kaiser hospital and another commercial insurer only through insurer competition for enrollees. Furthermore, Kaiser's competitiveness with respect to another insurer depends crucially on the proximity of potential enrollees to one of 27 Kaiser hospitals active in 2004; this varies considerably within a given market area, which would not be the case for another insurer which contracted with hundreds of hospitals.

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

However, as our theoretical bargaining model makes clear, the degree of competition between an insurer and Kaiser also affects negotiated prices along other dimensions. First, the presence of Kaiser in a market may depress insurer premiums which will have a negative effect on negotiated prices. Second, the attractiveness of Kaiser as an option affects not only the outside option of an

[3]This also motivates why we focus on Kaiser. Using proximity to hospitals for a different commercial insurer, which competed with BS, would impact the hospital-BS bargaining process through multiple routes as this different insurer might also have an existing contract with the hospital. Considering other commercial insurers in the regression analyses would therefore make the results more difficult to interpret.

insurer, but also that of the hospital. E.g., if a hospital is dropped from BS, some consumers may switch from BS to another insurer that still contracts with the hospital; however, if consumers switch to Kaiser, they cannot still access that hospital. This depresses negotiated prices. Furthermore, if a hospital negotiates with several commercial insurers, the impact of Kaiser's presence on each of these individual bilateral bargains will have reinforcing effects across all bargains. Overall, then, the net impact of Kaiser competition on prices is ambiguous.

In addition to our Kaiser variable, we use a prediction of how consumers' willingness-to-pay (WTP) for an insurer's network changes when a particular hospital is removed from it (Capps et al. (2003)). This "ΔWTP" variable, developed in the previous literature on hospital-insurer bargaining, is computed from the estimated demand system.[4] Our Kaiser variable measures the extent to which consumers may view Kaiser as a possible substitute for their current insurer, while ΔWTP captures the extent to which consumers wish to find a substitute when a particular hospital is dropped. This intuition prompts us also to interact the two variables in order to capture possible heterogeneous effects of insurer competition. Since consumers will be more likely to switch away from an insurer that drops a more attractive hospital from its network, the impact of Kaiser presence on negotiated prices may be positive for the most attractive hospitals (as measured by ΔWTP) but negative for other providers.

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. Furthermore, we argue that variation in employer choice sets and the competitiveness of other commercial insurers is likely to be well captured by market controls, and unlikely to vary systematically at the same 3 mile radii used to measure Kaiser attractiveness.

Our results support the hypothesis that insurer competition is an important determinant of hospital prices. They also indicate that the effect is heterogeneous across hospitals. The average effect of Kaiser presence on a hospital's negotiated prices is negative for most hospitals. However, for hospitals in the top quartile of our ΔWTP measure, increasing the proportion of patients with local access to a Kaiser hospital by 10% results in an increase in the negotiated price per admission of approximately $120, or 2% of the average hospital price per admission in our data. We conclude that a complete analysis of the impact of health insurer competition should take heterogeneous hospital price effects into account.

[4] The previous hospital bargaining literature used 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.

1.1 Related Literature

This paper is related to a previous literature considering the relationship between insurer competition and provider prices. One of the most recent of these papers, Moriya et al. (2010), reviews previous studies that find, in general, that increases in insurer competition are associated with increases in hospital prices. However most previous studies analyzed either the impact of insurer market power on prices, or that of hospital market power, but not both. The authors then analyze a dataset from Medstat containing transaction prices for health care services. They use a structure-conduct-performance approach, regressing prices on hospital and insurer concentration (measured by Herfindahl indices) and using the panel structure of their data to difference out market and firm fixed effects. They 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; "it is best thought of as an empirical exploration of the idea" that concentration among buyers, and among sellers, should be reflected in prices. Melnick et al. (2010) conduct a very similar analysis 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.

There is another section of the literature that models the bargaining between insurers and hospitals. Early papers including Town and Vistnes (2001) and Capps et al. (2003) estimate specifications that are consistent with an underlying bargaining model but do not fully specify that model (particularly the effect of insurer competition on the bargaining outcome). Sorensen (2003) provides reduced form evidence that insurers with a better ability to channel patients to certain hospitals negotiate lower prices. Gowrisankaran et al. (2013) and Lewis and Pflum (2013) both estimate fully-specified bargaining models and make important contributions to this literature; the former paper considers the impact of bargaining on the prices of hospital systems while the latter focuses on modeling the consequences of mergers. Dranove et al. (2008) develops a dynamic model of the bargaining process. All three of these papers assume that consumers cannot switch plans in response to the bargaining outcome. Ho (2006, 2009) relax this assumption and estimate a model of consumer demand for hospitals, and for insurers given the network of hospitals offered, as an input to a model of hospital network formation (assuming a take-it-or-leave-it offers model to determine hospital prices). Lee and Fong (2012) contains a dynamic bargaining model that allows consumers to switch insurers but has not yet been taken to data.

Our contribution to this literature is to bring the finding of the first set of papers—that insurer competition has a demonstrable effect on provider prices—into the bargaining framework developed in the second set. We write down a theoretical bargaining model that includes the effect of insurer competition, in addition to the effect of hospitals competing for inclusion in insurer networks, and use it to derive an equation that can be empirically estimated. We demonstrate that consumers' ability to move across insurers has an empirically-relevant and heterogeneous impact on hospital prices, controlling explicitly for other bargaining effects.

Our research is also related to recent work finding that insurer market power can affect premiums. Dafny et al. (2012) find that greater concentration resulting from a merger of insurers is associated with a modest increase in premiums, suggesting that insurers are not passing on the cost savings from decreased hospital prices to their enrollees. Dafny (2010) finds evidence consistent with this. Our finding that the input price effect of insurer competition is heterogeneous across hospitals helps reconcile the two literatures. Our estimates suggest that only very attractive hospitals' prices increase substantially with insurer competition. Thus, if the insurance market becomes less competitive and more concentrated, the average reduction in hospital paymentsmay simply not be large enough to outweigh the impact of reduced 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)). In a related industry, recent empirical work by Ellison and Snyder (2010) find that large drugstores secure lower prices from competing suppliers of antibiotics.

2 Theoretical Model

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

2.1 A Simple Bargaining Model

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

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

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

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

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

4. Patients become sick with probability γ; those that are sick visit some hospital in their network. (In our empirical application, we will allow for heterogeneous consumers who become

sick with different diagnoses with different probabilities; consumers will have different preferences for hospitals depending on their diagnosis.)

Consider hospital $i \in \mathcal{H}$ bargaining with MCO $j \in \mathcal{M}$. Define profits for MCO j to be:

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

where D_j is MCO j's demand (number of enrollees) and $\sigma_{hj}(\mathcal{G})$ is the share of MCO j's patients choosing hospital h. Since we assume bargains happen simultaneously, if hospital i comes to a disagreement with MCO j, we assume the new network is $\tilde{\mathcal{G}} \equiv \{\mathcal{G} \setminus ij\}$, and MCO j receives its disagreement payoffs (or outside option):

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

Similarly, define profits for hospital i (and its disagreement profits from dropping MCO j) to be:

$$\pi_{i,\mathcal{H}}(\boldsymbol{p}, \mathcal{G}) = \gamma \sum_{m \in \ \mathcal{G}_{\rangle,\mathcal{H}}} D_m(\boldsymbol{\phi}(\boldsymbol{p}, \mathcal{G}), \mathcal{G}) \sigma_{i,m}(\mathcal{G})(p_{im} - c_{im})$$
$$\pi_{i,\mathcal{H}}(\boldsymbol{p}_{-ij}, \tilde{\mathcal{G}}) = \gamma \sum_{m \in \tilde{\mathcal{G}}_{i,\mathcal{H}}} D_m(\boldsymbol{\phi}(\boldsymbol{p}_{-ij}, \tilde{\mathcal{G}}), \tilde{\mathcal{G}}) \sigma_{im}(\tilde{\mathcal{G}})(p_{im} - c_{im})$$

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

We assume prices $p_{ij} \in \boldsymbol{p}$ are negotiated for all $ij \in \mathcal{G}$ via simultaneous bilateral Nash bargaining such that:

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

Thus, each price p_{ij} maximizes the hospital i and MCO j's bilateral Nash product given all other prices $\boldsymbol{p}_{-ij}$. This assumption has been proposed in Horn and Wolinsky (1988) , and since used in applied work including Crawford and Yurukoglu (2012), Grennan (2013), Gowrisankaran et al. (2013), Lee and Fong (2012).[5] We assume Nash bargaining parameters $\{\tau_M, \tau_H\}$ for MCOs and hospitals are the same across agents of the same type, and $\tau_M + \tau_H = 1$.

To simplify our analysis, we make the following additional assumptions:

1. Consumer choices only respond to the prices that hospitals charge insurers through their response to premiums $\boldsymbol{\phi}(\cdot)$; once enrolled with an MCO, consumers are not influenced by hospital prices in choosing which hospital to visit. That is, the quantity and selection of

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

consumer types onto hospitals is not directly affected by $\boldsymbol{p}$ conditional on premiums. Note that this has implicitly been assumed in the construction of the profit functions: both demand for insurers (D_j) and demand within an insurer for a hospital (σ_{ij}) is only a function of the network and premiums $\boldsymbol{\phi}$. 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).

2. Premiums do not respond to (small) changes in negotiated prices p_{ij}: i.e., $\frac{\partial \phi_k}{\partial p_{ij}} \approx 0$ for all $j, k \in \mathcal{M}$, $i \in \mathcal{H}$. First, we assume prices are privately observed by each insurer-hospital pair; changes in equilibrium prices p_{ij} will thus not affect premiums for other insurers $-\boldsymbol{j}$. Second, we assume premiums for a given insurer j do not respond to small changes in a given hospital's prices p^*_{ij}; this is consistent with premiums being set across large geographic regions (e.g., all of Southern California) and individual hospital market shares across the entire region as being small. However, we allow for the possibility that premiums can adjust if the network $\mathcal{G}$ changes (holding fixed prices): i.e., $\boldsymbol{\phi}(\boldsymbol{p}, \mathcal{G})$ may be different from $\boldsymbol{\phi}(\boldsymbol{p}_{-ij}, \mathcal{G} \setminus ij)$.

Under these assumptions, the FOC of the maximization problem given by (1) implies the following linear equation for prices:

$$
\begin{aligned}
p^*_{ij} = & \tau_H \left[\frac{D_j \phi_j - \tilde{D}_j \tilde{\phi}_j}{D_j \gamma \sigma_{ij}} - \left(\frac{\sum_{h \in \mathcal{G}_j \setminus ij} p^*_{hj} \gamma (\sigma_{hj} - \frac{\tilde{D}_j}{D_j} \tilde{\sigma}_{hj})}{\gamma \sigma_{ij}} \right) \right] \\
& + \tau_M \left[c_{ij} - \frac{\sum_{m \in \tilde{\mathcal{G}}_i} (D_m \sigma_{im} - \tilde{D}_m \tilde{\sigma}_{im})(p^*_{im} - c_{im})}{D_j \sigma_{ij}} \right].
\end{aligned}
\tag{2}
$$

where we have dropped the arguments of D_j, ϕ_j, and σ_{ij} for expositional convenience, and have used $(\tilde{\cdot})$ to denote functions which take as arguments $\mathcal{G} \setminus ij$ (and potentially $\boldsymbol{p}_{-ij}$): e.g., $\tilde{\phi}_j \equiv \phi_j(\boldsymbol{p}_{-ij}, \tilde{\mathcal{G}})$. We rearrange (2) and multiply through by $\gamma \sigma_{ij}$ (the fraction of MCO j's enrollees that visit hospital i) so that the LHS of the equation is in terms of payment from j to i per enrollee rather than per admission:

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

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

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

We assume ω_{ij} is a mean zero independently distributed cost shock, and 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.

Discussion Equation (3) expresses the price paid from MCO j to hospital i in terms of the change in each firm's outside options due to disagreement. The first line represents changes to MCO j's gains from trade. Term (i) represents j's changes in premium revenue upon losing hospital i due to fewer patients being enrolled and lower premiums; the greater the loss, the higher is p^*_{ij}. Term (ii) represents the change in payments per enrollee j makes to other hospitals on its existing network upon losing i. The first part of (ii), $\sum_{h\in\mathcal{G}_j\setminus ij} p^*_{hj}\gamma(\sigma_{hj} - \tilde{\sigma}_{hj})$, 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), $\sum_{h\in\mathcal{G}_j\setminus ij} p^*_{hj}\gamma(\frac{D_j - \tilde{D}}{D_j}\tilde{\sigma}_{hj})$, adjusts for the fact that fewer patients are now enrolled in j. Term (ii) indicates that if j's enrollees visit higher cost hospitals on j's network if i is dropped, then p^*_{ij} is higher.

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

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

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

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

$$\boldsymbol{p} \odot \gamma\boldsymbol{\sigma} = \tau_H [\underbrace{\boldsymbol{\phi}^{\Delta}}_{(i)} - \underbrace{\boldsymbol{\Sigma}^{\boldsymbol{\Delta}}\boldsymbol{p}}_{(iia)} - \underbrace{\boldsymbol{D}^{\boldsymbol{\Delta}} \odot (\boldsymbol{\Sigma p})}_{(iib)}] + \tau_M [\underbrace{\boldsymbol{c} \odot \gamma\boldsymbol{\sigma}}_{(iii)} - \underbrace{\boldsymbol{\Sigma}^{\boldsymbol{D}}(\boldsymbol{p} - \boldsymbol{c})}_{(iv)}] + \boldsymbol{\epsilon} \tag{5}$$

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:

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

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

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

The elements of (5) labelled $(i) - (iv)$ correspond to the elements of (3), where (ii) has been decomposed into two different parts, (iia) and (iib). Equation (5) will inform our estimation approach in the next section. We will be able to measure directly the LHS and terms (iia) and (iii) of (5); we will proxy for terms (i), (iib), and (iv) by using constructed variables described in the next section. Since negotiated prices enter both sides of (5), we will estimate this system of equations using instruments.

3 Empirical Application

In the absence of a natural experiment to identify the impact of insurer competition on hospital prices we leverage the relationship between equilibrium negotiated prices and determinants of consumer demand for insurers and hospitals derived from our theoretical model in (5). Our approach is to 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. We use an estimated hospital demand model, and data on hospital and insurer characteristics, to predict as many of the remaining terms in (5) as we can. We wish to provide evidence that plausibly exogenous differences in insurer competitiveness across hospitals have an economically significant effect on negotiated prices. If insurer competition did not matter (for example if consumers were captive to an insurer and did not switch in response to hospital network changes, or if firms did not internalize this possibility), then we would not expect to find any impact of our insurer competitiveness variables on prices.

In this section we will first discuss the data from which negotiated prices, average hospital costs, and insurer-hospital networks can be inferred. We then will specify and estimate a model of consumer demand for hospitals from which we can predict the share of consumers who visit any hospital h from MCO j after a change in the observed network (i.e., $\{\sigma_{hj}(\mathcal{G} \setminus ij)\}_{\forall i,h \in \mathcal{G}_{j,\mathcal{M}}; j \in \mathcal{M}}$). This will allow us to construct measures of terms (iia) and (iii) in equation (5).

We do not directly observe or predict the changes in insurer demand and premiums (terms (i) and (iib) in (5)) or in hospital payments from other insurers (term (iv)) when a hospital is dropped from an insurer's network. We adopt the approach of proxying for these terms using the Kaiser and ΔWTP variables, rather than estimating a model of insurer demand and premium setting to explicitly control for them, for several reasons. First we view our approach as a direct way to demonstrate that insurer competition is important without making the assumptions needed to estimate such a model. In addition we do not have access to all the data that would be needed to estimate insurer demand. For example Health Net and Pacificare are large insurers in California that are not observed in our data; we therefore cannot credibly estimate preferences over these insurers.[6] Similarly, only limited data on premiums are available and there is significant (unobserved) variation across employers in the terms of employee contributions and whether they are self-insured, both of which should be accounted for in the premium-setting model.

Instead we proxy for the impact of network changes on MCO demand and premiums using variables that capture how likely consumers are to leave insurer j if hospital i is dropped. As noted above, the first variable is a measure of the presence of Kaiser Permanente in the hospital's

[6] We note that each insurer's network and hospital prices apply to all employers offering the insurer to their employees, not just to the agency in our data. The demand and price changes in (5) therefore refer to total changes for the insurer, and for the hospital, when network changes take place. While we assume that our hospital demand model (estimated using our agency's enrollees for each of Blue Cross and Blue Shield's hospital networks) does a reasonable job of estimating the preferences of all enrollees of those two insurers, and therefore predicting the overall change in demand for hospitals from these insurers after a network change (and this is all that is needed for terms (iia) and (iii) of the equation), an analogous assumption cannot be made for insurer demand. In addition a realistic model would need to capture employer-insurer negotiation dynamics; this is beyond the scope of this and many papers.

market. Specifically we use the share of each hospital's patients who live within 3 miles of a Kaiser Permanente hospital. The second measure is the change in consumer willingness to pay for MCO j's network if hospital i is removed. This term, ΔWTP_{ij}, was introduced in Capps et al. (2003), and accounts for both the "quality" of a hospital relative to others in the market and the existence of a viable substitute in the network. Both these terms, as well as their interactions, should affect how an insurer's demand D_j and premium ϕ_j would change subsequent to a disagreement with a hospital.

In Section 3.5, we present the estimating equation based on (5) 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 over 1M California public employees, retirees, and their families. The claims are aggregated into hospital admissions and assigned a MS-DRG diagnosis 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 on BS and BC which we use to estimate a model of consumer demand (described in the next section). We divide each price by the 2004 DRG Medicare weights to account for differences in relative values across diagnosis; this controls for case mix and utilization differences across hospitals in obtaining a measure of insurer-hospital price per patient.[7] 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.

The network of hospitals on BS and BC were obtained directly from the insurers for 2004. We take hospital characteristics from the American Hospital Association (AHA) survey and demographic information from the 2000 Census.

Many employers, including CalPERS, offer access to Kaiser Permanente in some markets but we do not observe prices or claims information for Kaiser enrollees. We obtained location information for Kaiser hospitals in California in 1995 and 2004 from the AHA survey. 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 offered by BS and BC which are located in the 4 HSAs containing San Francisco, Oakland, Los Angeles, and San Diego. 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; we are concerned that hospital pricing

[7] 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 resource utilization across hospitals in constructing comparable average prices. See also the discussion in Gowrisankaran et al. (2013).

in these areas may be subject to unobservables that are difficult to control for. This leaves us with a sample of 221 hospital-insurer price observations (132 from BC, 89 from BS), comprising 144 unique hospitals.

3.2 Consumer Demand for Hospitals

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

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

where δ_i are captured by hospital fixed effects, z_i are observed hospital characteristics, $\upsilon_{i,l}$ are observed characteristics of the consumer such as diagnosis and location and $\varepsilon^D_{i,h,l}$ 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 hospital for a particular diagnosis.[8] We estimate the same 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.

Further details on the demand model, together with estimates, are given in Appendix 1.

3.3 Willingness-to-Pay

We follow previous papers such as Capps et al. (2003) and Farrell et al. (2011) by using a measure of consumer willingness-to-pay (WTP) for a hospital on a network as a proxy for the change in consumer surplus when the hospital is dropped from a network; this, combined with our measure of insurer competition, will in turn proxy for the change in demand and hence premiums if a hospital is dropped.

We use the estimated demand model to predict the WTP variable for our application: the change in consumer WTP when a hospital is added to the network observed for Blue Shield or Blue Cross in 2004. Individual k's expected utility from the hospital network offered by plan j when he

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

has diagnosis l is calculated 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 knowing whether or not he will be sick), individual k's expected benefit from having i in network is given by:

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

where γ_k^a is the probability that consumer k is admitted to hospital (conditional on age and gender) and $\gamma_{k,l}$ is the probability of diagnosis l conditional on admission, age and gender.[9] Finally, we take a weighted average over the commercially insured population of the market to generate the WTP measure that we will use in our analysis:

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

where $N_{k,m}$ is the commercially-insured population of market m in age-gender-zipcode group k.

It is worth stressing that although we refer to ΔWTP as the change in consumers' willingness-to-*pay* for an insurer's network, it is measured in utils and not dollars as no conversion has been made. Nonetheless, the relative differences across hospitals' ΔWTP values will be informative.

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

[9] Probabilities γ_k^a are generated 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. An alternative method, using CalPERS data for both numerator and denominator, generated similar results. The $p_{k,l}$ are the realized probabilities for commercially insured patients in California taken from OSHPD discharge data for 2003.

the main regression equation) takes account of predicted changes in the proportions of different enrollee types visiting each hospital, their probabilities of admission and the cost of each hospital, after this network change.

3.4 Measure of Insurer Competition: Kaiser

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 share of hospital i's patients who come from zipcodes that are within 3 miles of a Kaiser Permanente hospital. Specifically, we use the OSHPD 2003 data to define the catchment area of each hospital as the set of zipcodes 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 zipcode in the OSHPD data.

The idea behind this strategy is that, the higher the value of this variable, the more likely enrollees of MCO j will be to switch to Kaiser insurance on losing access to hospital i. Kaiser is the largest MCO in the US; it had 37% of the HMO market in California in 2004. However its convenience to patients differs substantially across geographic areas, particularly since it is a vertically integrated insurer that owned only 27 hospitals in California in 2004, but rarely offers 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; 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. Further details are given below.

In section 4.1 we provide results using alternative measures of Kaiser competitiveness including different distance measures.

3.5 Regression Equations

Equations (3)-(5) from the bargaining model developed in the previous section motivates the following regression equation:

$$
\begin{aligned}
\underbrace{P_{ij}}_{\hat{p}_{ij}\widehat{\gamma\sigma}_{ij}} = {} & \alpha_1 \underbrace{\text{Cost}_{ij}}_{\bar{c}_i\widehat{\gamma\sigma}_{ij}} + \alpha_2 \underbrace{\Delta Pmt_{j,\setminus ij}}_{\sum_{h\in\mathcal{G}_j\setminus ij}\hat{p}_{hj}(\widehat{\gamma\sigma_{hj}} - \widehat{\gamma\tilde{\sigma}_{hj}})} \\
& + \alpha_3 \Delta WTP_{ij} + [\alpha_4 \underbrace{Pmt_{j,\setminus ij}}_{\sum_{h\in\mathcal{G}_j\setminus ij}\hat{p}_{hj}(\widehat{\gamma\tilde{\sigma}_{hj}})} + \alpha_5 Kaiser_i + \alpha_6 Kaiser_i \times Pmt_{j,\setminus ij}] \\
& + \Delta WTP_{ij} \times [\alpha_7 Pmt_{j,\setminus ij} + \alpha_8 Kaiser_i + \alpha_9 \Delta Kaiser_i \times Pmt_{j,\setminus ij}] \\
& + \boldsymbol{HSA}_m + BS_j + \boldsymbol{\beta} \times \boldsymbol{demogs}_i + \varepsilon_{ij}.
\end{aligned} \quad (6)
$$

Here $P_{ij} \equiv \hat{p}_{ij}\widehat{\gamma\sigma}_{ij}$ is the dependent variable in (5) and corresponds to the observed payment made to hospital i by MCO j per enrollee.[10]

Two of the right-hand-side variables in equation (5) are included explicitly in the regression: these are hospital i's average cost per enrollee of MCO j ($\text{Cost}_{ij} \equiv \bar{c}_i\widehat{\gamma\sigma}_{ij}$), and the change in MCO j's payments per enrollee to other hospitals when hospital i is dropped from j's network ($\Delta Pmt_{j,\setminus ij}$). The cost term, like the prices, is weighted by $\widehat{\gamma\sigma}_{ij}$ 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 $\{\tau_H, \tau_M\}$, the hospital and insurer bargaining parameters, in (5); we later test and cannot reject the restriction $\alpha_1 + \alpha_2 = 1$, thereby providing a check on our model specification.

The next two lines in (6) contain variables which are meant to proxy for the terms in (5) which interact with changes in insurer demand ($D_j(\mathcal{G}, \cdot) - D_j(\mathcal{G} \setminus ij, \cdot)$) and premiums ($\phi_j(\mathcal{G}) - \phi_j(\mathcal{G} \setminus ij)$) upon disagreement: i.e., terms (i), (iib), and (iv). In order, these variables are ΔWTP_{ij}, the change in a consumer's willingness-to-pay (in utils) for MCO j's network if hospital i is dropped; $Pmt_{j\setminus ij}$, the payment made to other hospitals in the network when hospital i has been dropped (again calculated using predicted market shares generated from our demand estimates); and $Kaiser_i$, our measure of Kaiser competitiveness (i.e., the share of admits to hospital i who live within 3 miles of a Kaiser hospital).

Much of the previous literature on hospital-insurer bargaining has used ΔWTP_{ij} to proxy for a MCO's premium change when a hospital is removed from the network absent insurer competition effects (Capps et al. (2003); Gowrisankaran et al. (2013)).[11] However, it is likely also to help capture the extent to which an insurer's demand is influenced by the network change. That is, the impact of insurer competition is likely to be greatest for hospitals with high perceived quality (high ΔWTP_{ij}). We allow for this possibility by interacting the variables in the first set of parentheses in (6) with ΔWTP_{ij}.

We also include HSA fixed effects $\boldsymbol{HSA}_m$, an indicator that distinguishes between insurers BS_j, and demographic controls for the hospital's zip code, $\boldsymbol{demogs}_i$.[12] The HSA fixed effects control for any unobserved market-level factors which influence demand for insurers: these could include, for example, the availability of other insurers in the market or the size of the menu of insurance plans offered by employers in the area. As noted in Dafny et al. (2013), these menus are often small: in their national data in 2004 only around 25% of large employers offered more than 2 plans to

[10] As in the construction of our ΔWTP measure, we construct $\widehat{\gamma\sigma}_{ij}$ using weighted averages over age groups and diagnoses for enrollees of MCO j.

[11] 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.

[12] We have data for only 2 insurers so our insurer fixed effects comprise just an indicator for Blue Shield. 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.

their employees. While employers can change their plan menus in response to changes in hospital networks, variation in current menus across employers will clearly affect the ability of consumers to switch plans and therefore impact of insurer competition on hospital prices. We assume that average employer offerings are fixed across zip codes within an HSA so that this variation will be absorbed in our HSA fixed effects.

3.6 Estimation and Identification

The econometric error in (6) $\varepsilon_{ij} \equiv \epsilon_{ij} + \nu_{ij}$ will include two sources of error. The first, ϵ_{ij}, is the MCO-hospital specific cost shock defined in (4). The second, ν_{ij}, represents the error introduced by utilizing proxies for terms (i), (iib), and (iv) in our estimating equation (6). It will contain any elements of these which are not controlled for by the observables on the last three lines of equation (6), market-level and insurer fixed effects and demographic controls, as well as interactions of ΔWTP_{ij}, $Pmt_{j,\setminus ij}$, and $Kaiser_i$. In essence, ν_{ij} captures unobserved differences in how consumers substitute across insurers that we have not explicitly controlled for.

We estimate (6) using 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 (6) that are not functions of prices: i.e., 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:

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

interacted with a constant, ΔWTP_{ij}, $Kaiser_i$, and $\Delta WTP_{ij} \times Kaiser_i$; this provides 16 excluded instruments in $\boldsymbol{Z}$. These additional instruments, comprising functions of costs and ΔWTP of other hospitals in an insurer's network, are correlated with an insurer's payments to other hospitals.[13]

As we have assumed $\omega_{ij} \equiv c_{ij} - \bar{c}_i$ is independent and mean zero, ϵ_{ij} will be orthogonal to non-price variables on the RHS of (6) 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 (6)) 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} and will be valid instruments.

Identification of Kaiser Terms: Our analysis relies on the exogeneity of $Kaiser_i$ with respect to other variables we have not controlled for that could shift prices. In particular, the elements of terms (i), (iib), and (iv) which could cause problems include the presence and competitiveness of other insurance plans. These are also a function of the choice sets offered by employers. As noted above, such factors will affect the extent to which consumers can switch plans; if correlated

[13]First-stage F-stats for all instrumented variables are greater than 10.

with Kaiser presence they will affect the interpretation of our estimates. However, we assume this variation across markets is well captured by market fixed effects and demographic controls. This is consistent with the desirability of other insurers being smoother within an HSA than that of Kaiser, for example because other insurers contract with many more than Kaiser's 27 hospitals in CA. 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.

To account for the possibility that Kaiser responded to local demand shocks when choosing locations for its hospitals, and these demand shocks also affected insurer competition, we also run the analysis using the location of Kaiser hospitals in 1995. This exercise assumes that ten year lagged hospital locations are unlikely to be correlated with 2004 demand shocks. Any factors affecting location decisions that are serially correlated over time are assumed to be adequately controlled for using HSA fixed effects and zip code level demographic controls.

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

4 Estimation Results

We begin with summary statistics of our data in Table 1. The average price paid per enrollee is \$21.43 (standard deviation 27.6); this corresponds to an average price per patient of \$5677 (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 \$21.89 on average and total other hospital payments increase to \$322.64. We use payroll expenses per admission as our hospital cost measure; we regard it as a reasonable proxy for resource use on the particular patient. The mean expense per enrollee is \$19.66 (standard deviation \$23.02). Finally the mean ΔWTP_{ij} is 0.095 (standard deviation 0.12), and the mean fraction of a hospital's patients that are within 3 miles of a Kaiser hospital is .055 (standard deviation .103) in 2004.

Table 2 compares the characteristics of Kaiser hospitals to those of the hospitals included in our regressions. We wish to provide evidence that Kaiser hospitals are sufficiently similar to other hospitals to justify our assumption that consumers consider Kaiser insurance to be a reasonable substitute for Blue Shield or Blue Cross. We exclude from this comparison both non-Kaiser and Kaiser hospitals located in San Francisco, Oakland, Los Angeles, and San Diego, since these HSAs are not included in our regression analysis. The table indicates that there are some differences on average between the remaining 11 Kaiser hospitals and the others in our data. Kaiser hospitals are larger, with 214 beds on average compared to 163 for other hospitals. They have more nurses per bed and more physicians per bed. Their service provision is similar to that of other hospitals in many cases: for example 64% of Kaiser hospitals provide CT scans compared to 63% of other hospitals. 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

Table 1: Summary Statistics

	Mean	S.D.
Price per enrollee ($)	21.43	27.56
ΔWTP	0.10	0.12
Other-hospital total payment per enrollee ($)	322.64	97.83
Δother-hospital payment per enrollee ($)	-21.89	26.34
Hospital cost per enrollee ($)	19.66	23.02
Blue Shield	0.40	0.49
(3mi) $Kaiser_i$ (2004)	0.06	0.10
(3mi) $Kaiser_i$ (1995)	0.04	0.08
N	221	

Notes: Summary statistics on the dataset used to run price regressions. N=221 hospital-insurer pairs. All costs and prices rescaled to $ per enrollee (accounting for probability of admission to hospital conditional on age and gender)

Table 2: Characteristics of Kaiser and Other Hospitals

	Non-Kaiser Hospitals	Kaiser Hospitals
Number of beds	163.4 (123.2)	214.3 (112.6)
Nurses per bed	1.25 (0.54)	1.81 (0.66)
Physicians per bed	0.04 (0.09)	0.52 (0.65)
Offer CT scans	0.63 (0.48)	0.64 (0.50)
Offer PET scans	0.10 (0.30)	0.18 (0.40)
Have a NICU	0.26 (0.44)	0.36 (0.50)
Offer angioplasty	0.28 (0.45)	0.09 (0.30)
Offer oncology services	0.43 (0.50)	0.55 (0.52)

Notes: Summary statistics comparing the hospitals in our price regressions to the Kaiser hospitals in our data. N=144 non-Kaiser hospitals and 11 Kaiser hospitals. Providers located in San Francisco, Oakland, Los Angeles and San Diego are excluded. Characteristics taken from the American Hospital Association data 2003-4.

listed in our data, are 18% and 10% respectively. Birthing services are also provided in substantially more Kaiser hospitals: 36% of Kaiser facilities in our data have a neonatal intensive care unit, for example, compared to 26% of other hospitals. We conclude that there is no clear evidence in our data that Kaiser should be regarded as a poor substitute for other health insurers.

Tables 3-4 contain our regression results. Standard errors are clustered by hospital.[14] Table 3 excludes terms with $Kaiser_i$ and interaction terms in (6), but includes all market, insurer, and demographic controls. We begin in Model 1 in 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 WTP and cost variables. When we add $\Delta Pmt_{j,\setminus ij}$, this has the expected negative and significant coefficient but ΔWTP falls in magnitude and becomes insignificant (suggesting that high-ΔWTP hospitals have relatively high-priced substitutes). These effects are consistent with the predictions of our bargaining model laid out in (3). We note, however, that ΔWTP is positive and significant when we include the whole sample of California markets. The reduced significance of our results when we restrict our attention to HSAs other than Los Angeles,

[14] Clustering by insurer-market resulted in broadly similar results 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}	67.26**	28.28	1.635	21.09	2.107
	(31.03)	(35.73)	(24.85)	(32.04)	(24.67)
$HospitalCost_{ij}$	0.712***	0.395***	0.327**	0.348***	0.284
	(0.161)	(0.113)	(0.157)	(0.110)	(0.174)
$\Delta Pmt_{j,\setminus ij}$		-0.494***	-0.666***	-0.575***	-0.709***
		(0.153)	(0.128)	(0.136)	(0.146)
$Pmt_{j,\setminus ij}$				-0.0521***	-0.0134
				(0.0172)	(0.0235)
Observations	221	221	221	221	221
Adjusted R^2	0.797	0.830	0.825	0.840	0.828

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

Notes: Results for regression equation (6). Dependent variable is expected price per enrollee paid by insurer j to hospital i. $\Delta\,\mathrm{Pr}\,ice$ is the change in expected payments to other hospitals, per enrollee, if hospital i is dropped from the network. "Hospital cost" is the cost of hospital i weighted by the average probability that an enrollee in insurer j will be admitted to hospital i. ΔWTP is the consumer willingness-to-pay for hospital i to be added to insurer j's network; see Section 2 for details. Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

San Francisco / East Bay and San Diego suggests that the leverage gained from attractiveness to patients may be greater in urban markets where patients have easier access to a larger number of hospitals. Adding in instruments changes the magnitude of the predicted coefficients but the changes are not significant.

Model 3 in Table 3 contains our first test of the importance of insurer competition. We add $Pmt_{j,\setminus ij}$ which occurs in two places in equation (3): it is contained in $\Delta Pmt_{j,\setminus ij}$, and (separately) is interacted 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 results support this: the coefficient on $Pmt_{j,\setminus ij}$ is negative; however, the coefficient is not significant once instruments are used.

Table 4 reports results when we add additional terms to proxy for insurer competition. Even if consumers can move across insurers in response to network changes, switching costs such as the need to change primary physicians may lead them to choose to move only when very attractive hospitals are dropped. Model 4 in the table therefore adds our $Kaiser_i$ and $Pmt_{j,\setminus ij}$ as well as ΔWTP_{ij} and interaction terms. The results are consistent with our hypothesis: the $Kaiser_i * \Delta WTP_{ij}$ coefficient is positive, while its interaction with $Pmt_{j,\setminus ij}$ is negative; both are significant at the 1% level.

Model 4 IV also reports statistically significant coefficients on $Cost_{ij}$ and $\Delta Pmt_{j,\setminus ij}$; as discussed earlier, the coefficients on these terms correspond to the bargaining weights $\{\tau_M, \tau_H\}$ of MCOs

Table 4: Price Regressions including Insurer Competition Measure

	(1) Model 4	(2) Model 4 IV
ΔWTP_{ij}	-2.616	-12.63
	(27.59)	(34.07)
$HospitalCost_{ij}$	0.390***	0.349***
	(0.106)	(0.0981)
$\Delta Pmt_{j,\setminus ij}$	-0.643***	-0.640***
	(0.117)	(0.0917)
$Pmt_{j,\setminus ij}$	-0.0352**	-0.0207
	(0.0166)	(0.0195)
(3mi) $Kaiser_i$	-89.78*	-159.2*
	(50.50)	(88.15)
(3mi) $Kaiser_i * \Delta WTP_{ij}$	1086.9***	1189.3***
	(125.4)	(187.7)
(3mi) $Kaiser_i * Pmt_{j,\setminus ij}$	0.246	0.454*
	(0.151)	(0.273)
(3mi) $Kaiser_i * \Delta WTP_{ij} * Pmt_{j,\setminus ij}$	-3.147***	-3.382***
	(0.411)	(0.575)
$\Delta WTP_{ij} * Pmt_{j,\setminus ij}$	-0.00564	0.00987
	(0.0639)	(0.0710)
Observations	221	221
Adjusted R^2	0.885	0.880

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

Notes: Results for regression equation (6). Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

and hospitals from our bargaining model in (3). The sum of these two estimated coefficients is very close to 1, consistent with our model. Furthermore, these estimates indicate that hospitals have a slightly higher bargaining weight than MCOs (although equal weights cannot be rejected).

4.1 Robustness

Tables 5 and 6 report results from our full model specification (Model 4 IV) while varying the distance by which the $Kaiser_i$ variable is defined: that is, in these tables, $Kaiser_i$ 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 (4) in Table 4. For distances 3-5 miles, coefficients on $HospitalCost_{ij}$, $\Delta Pmt_{j,\setminus ij}$, $Kaiser_i * \Delta WTP_{ij}$, and $Kaiser_i * \Delta WTP_{ij} * Pmt_{j,\setminus ij}$ are statistically significant and share the same sign. The estimated magnitude of the impact of Kaiser falls as the distance increases from 3 to 4 to 5 and finally to 7 miles.

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}	23.37	-12.63	-2.079	-8.120	32.75	14.18
	(51.33)	(34.07)	(45.99)	(45.39)	(55.38)	(58.94)
$HospitalCost_{ij}$	0.336***	0.349***	0.336***	0.293***	0.317***	0.344***
	(0.105)	(0.0981)	(0.101)	(0.0913)	(0.0955)	(0.0947)
$\Delta Pmt_{j,\setminus ij}$	-0.606***	-0.640***	-0.636***	-0.681***	-0.641***	-0.658***
	(0.104)	(0.0917)	(0.0940)	(0.0971)	(0.110)	(0.119)
$Pmt_{j,\setminus ij}$	-0.00858	-0.0207	-0.0195	-0.0212	-0.00728	-0.0169
	(0.0226)	(0.0195)	(0.0213)	(0.0218)	(0.0234)	(0.0232)
$Kaiser_i$	-130.6	-159.2*	-79.41	-48.12	-14.96	-16.09
	(159.3)	(88.15)	(62.31)	(36.03)	(26.76)	(16.68)
$Kaiser_i * Pmt_{j,\setminus ij}$	0.342	0.454*	0.211	0.122	0.0322	0.0444
	(0.488)	(0.273)	(0.199)	(0.115)	(0.0874)	(0.0544)
$Kaiser_i * \Delta WTP_{ij}$	1139.7	1189.3***	702.4**	415.1*	65.72	48.59
	(827.1)	(187.7)	(308.5)	(225.7)	(160.1)	(101.8)
$Kaiser_i * \Delta WTP_{ij} * Pmt_{j,\setminus ij}$	-3.031	-3.382***	-1.910**	-1.110*	-0.129	-0.135
	(2.476)	(0.575)	(0.914)	(0.649)	(0.471)	(0.300)
$\Delta WTP_{ij} * Pmt_{j,\setminus ij}$	-0.0738	0.00987	-0.0201	-0.00680	-0.110	-0.0629
	(0.123)	(0.0710)	(0.106)	(0.106)	(0.136)	(0.145)
Observations	221	221	221	221	221	221

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

Notes: GMM results for regression equation (6), 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.

To account for the possibility that recently opened Kaiser hospitals might have located based on demand shocks which could influence hospital prices, we repeat 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 are 25 active Kaiser hospitals in 1995, with 24 active in both 1995 and 2004.[15]

Table 6 reports results; estimates are broadly similar to our main specification.

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

Table 6: Price Regressions With Alternative Distances, Kaiser 1995 locations

	(1) 2 mi	(2) 3 mi	(3) 4 mi	(4) 5 mi	(5) 7 mi	(6) 10 mi
ΔWTP_{ij}	25.99	-4.024	8.518	-7.348	31.24	14.25
	(46.91)	(33.15)	(41.82)	(41.32)	(50.51)	(56.05)
$HospitalCost_{ij}$	0.348***	0.342***	0.315***	0.271***	0.306***	0.342***
	(0.105)	(0.0950)	(0.0996)	(0.0919)	(0.0934)	(0.0923)
$\Delta Pmt_{j,\setminus ij}$	-0.597***	-0.647***	-0.643***	-0.709***	-0.663***	-0.677***
	(0.100)	(0.0890)	(0.0952)	(0.0982)	(0.107)	(0.117)
$Pmt_{j,\setminus ij}$	-0.0138	-0.0190	-0.0192	-0.0255	-0.0120	-0.0180
	(0.0224)	(0.0199)	(0.0212)	(0.0216)	(0.0232)	(0.0230)
$Kaiser_i$	-34.33	-66.45	-30.35	-34.90	-3.098	-14.47
	(104.2)	(71.12)	(52.17)	(33.58)	(27.03)	(16.92)
$Kaiser_i * Pmt_{j,\setminus ij}$	-0.0158	0.192	0.0668	0.0834	-0.00344	0.0463
	(0.304)	(0.220)	(0.172)	(0.109)	(0.0919)	(0.0557)
$Kaiser_i * \Delta WTP_{ij}$	1049.6	999.2***	628.4**	429.9**	78.21	37.36
	(710.5)	(169.1)	(268.5)	(213.0)	(157.9)	(99.44)
$Kaiser_i * \Delta WTP_{ij} * Pmt_{j,\setminus ij}$	-2.638	-2.826***	-1.696**	-1.166*	-0.184	-0.121
	(2.072)	(0.515)	(0.794)	(0.604)	(0.467)	(0.295)
$\Delta WTP_{ij} * Pmt_{j,\setminus ij}$	-0.0881	-0.0160	-0.0430	-0.00823	-0.105	-0.0659
	(0.111)	(0.0693)	(0.0916)	(0.0889)	(0.119)	(0.136)
Observations	221	221	221	221	221	221

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

GMM results for regression equation (6), 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 that was opened prior to 1995. Standard errors are clustered by hospital. All regressions include market and insurer fixed effects and demographic controls.

5 Discussion

The results set out in Model 4 IV, Table 4, imply a negative effect of Kaiser availability on negotiated prices for most hospitals. We note that Kaiser presence may be associated with fiercer insurer competition in premiums, which the theory model would predict would lead to lower prices. In addition, if particular types of patients select into Kaiser (an effect that is not explicitly accounted for in our model), this could affect pricing in non-Kaiser hospitals and the direction of the effect is theoretically ambiguous. We also note two reasons why competition from Kaiser, in particular, could have a smaller or more negative effect on prices than competition from other insurers. First, by considering Kaiser rather than a different insurer, we lose the effect of consumers switching plans specifically in order to access a particular hospital that has been dropped from their plan's network. Instead a potentially smaller number of enrollees may switch because, given that they cannot access that hospital, they prefer to choose a different insurer and set of providers entirely. Second, since the hospital loses patients who switch to Kaiser, it is also worse off if it is dropped from the Blue Shield network. This might not be the case if we considered a different insurer which itself had a contract with the relevant hospital.[16] Our finding of a negative average effect of Kaiser availability on prices therefore does not contradict the previous literature that finds a positive effect of insurer competition more generally.

The magnitude of the estimated impact of Kaiser differs across hospitals, with a positive impact of Kaiser availability on prices for higher-ΔWTP hospitals. If we consider the hospitals above the 75th percentile of ΔWTP_{ij}, the results in Model 4 IV of Table 4 imply that increasing the share of a hospital's patients who have access to a Kaiser hospital within 3 miles of their zipcode by one standard deviation (.10) increases prices by \$118 on average (compared to a mean price of approximately \$5700). The average effect increases to \$195 for hospitals above the 90th percentile of WTP and \$228 for those above the 95th percentile.

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 impact on hospital prices, particularly for the hospitals that are most attractive to patients. We conclude that policy analysis concerning the importance of promoting competition between health insurers should take price effects into account.

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[16]The first of these points implies a smaller price effect for Kaiser than for other insurers; the second implies that the price effect for Kaiser could have a different sign.

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A Details of the Demand Model

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. Consumer k becomes ill with probability γ. 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, $\upsilon_{i,l}$ are observed characteristics of the consumer such as diagnosis and location and $\varepsilon^D_{i,h,l}$ is an idiosyncratic error term assumed to be iid Type 1 extreme value. 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).

We define five diagnosis categories using ICD-9-CM codes and MDC (Major Diagnosis Category) codes as shown in Table 7. 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 (variables that are missing for a particular hospital in one year are filled 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 8.

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

Table 9 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; the magnitudes are very similar 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 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

Table 7: 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 8: 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.

significant at p=0.1), and women in labor have a strong preference for hospitals with good labor services.

Table 9: 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.

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