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Hospital competition in HMO networks

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Abstract

We develop a framework for analyzing bargaining relationships between hospitals and HMOs under selective contracting. Using a unique dataset on hospitals in the Los Angeles area from 1990 to 1993, we estimate the determinants of actual negotiated prices paid to hospitals by two major HMOs. We find that a hospital's bargaining power, and thus its price, decrease when the HMO can readily turn to alternative networks that exclude the hospital. We simulate the effect of hypothetical hospital mergers on bargaining power and find that some hospital mergers, even in urban areas with many nearby hospitals, can lead to significant price increases. © 2001 Elsevier Science B.V. All rights reserved.

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1. Introduction

The ability of managed care plans to selectively contract with health care providers is an important means by which plans use to control costs. Through selective contracting, a managed care plan can credibly threaten to exclude providers such as hospitals, physicians, or pharmacies from its network, and thereby negotiate lower provider prices. [1] The ascendancy of managed care as the dominant form of private health insurance provision — over 70% of Americans with health insurance are enrolled in some form of managed care (Quinn, 1998) — highlights the importance of understanding the competitive interaction

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[1] A managed care plan defines a set of health care providers (the plan's "provider network") that its enrollees are given financial incentives to use. The most common types of managed care plans are health maintenance organizations (HMOs), point-of-service plans (POSs) and preferred provider organizations (PPOs).

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between managed care plans and health care. In this paper, we explore how one important type of health care provider, hospitals, compete in a selective contracting environment.

We develop an empirical framework in which hospitals, differentiated along geographic and other dimensions, compete for inclusion in a plan's network. Two important and interrelated questions emerge regarding the resulting hospital price competition. Firstly, how does the composition of a managed care plan's network affect hospitals' pricing incentives? Secondly, how do the preferences of a plan's enrollees for particular hospitals affect that plan's network formation strategy, and thus, hospital prices? We examine these questions using a unique dataset that includes the actual financial payments made by two large southern California HMOs to network hospitals.

Hospital competition has been the subject of much research. Most of the literature shows a correlation between competition and prices in markets where managed care is a significant player. [2] Our work extends this literature in two significant ways. Firstly, we explicitly consider several measures of hospital differentiation that have been largely ignored in the existing literature. [3] Secondly, our estimation methodology explicitly models the negotiations between hospitals and plans that determine hospital prices. We argue that a hospital's bargaining position with a plan, and hence its price, depend on the incremental value that hospital brings to the plan's network. A hospital's incremental value, in turn, is a function of the plan's opportunity cost of turning to its next-best alternative network that excludes the hospital. That opportunity cost depends importantly on how well the alternative network provides the scope of coverage the plan's enrollees want (in terms of both perceived quality and access). Thus, a hospital merger's effect may differ across plans depending upon the original configuration of the plan's hospital network and the plan's cost of reconfiguring that network.

We hypothesize that hospital prices are determined by a switching-regime framework representing the plan's two alternatives if faced with a price increase by a given hospital: either replace the hospital or drop the hospital without replacement. [4] A hospital's observed price should be a function of the incremental change in the value of the HMO's network, either from replacing the hospital with the next-best alternative hospital outside the network or from simply dropping the hospital from the network. A switching-regime framework provides a natural way to empirically implement this idea, as we can allow a hospital's price to be a function of two different possible regimes. Each regime represents the loss in value to the HMO of turning to one of its two possible alternative networks that excludes the hospital. The magnitude of that loss in network value, we hypothesize, is what constrains a hospital's price.

Our approach has significant implications for analyzing hospital competition. With HMOs contracting with multiple hospitals to form networks, a hospital's bargaining leverage depends both on its own characteristics and on the characteristics of other hospitals inside and outside the network. In particular, if the HMO's best alternative to contracting with

[2] For a complete survey of this literature, see Dranove and Satterthwaite (2000) or Gaynor and Vogt (2000).

[3] Dranove et al. (1993) and Zwanziger et al. (1990) address this point by considering how competition affects the differentiation decision of hospitals. See also Vistnes (1995) for discussion of the importance of differentiation in hospital antitrust analysis.

[4] As long as there are some switching costs associated with network reconfiguration, these two alternatives are more likely than a more radical network reconfiguration.

a high-priced hospital is to replace that hospital with another, the high-priced hospital's bargaining leverage depends on the hospital's incremental value to the network relative to other hospitals that could replace it. Thus, the hospital's incremental value will depend on the extent to which hospitals outside the network are good substitutes. But if the HMO's best alternative is instead to simply drop that hospital without replacing it, the hospital's leverage depends on the degree to which it adds value to the hospitals already included in the HMO's network.

We explore these predictions using data from three primary sources. Two large southern California HMOs provided confidential data on the payments they made to their network hospitals. This constitutes a unique source, in that few studies of hospital competition have been able to examine empirical pricing relationships using data on actual financial transactions between hospitals and managed care plans. [5] We supplement these data with patient discharge and hospital information supplied by the State of California.

We analyze the determinants of the bargaining position of general acute care hospitals in Los Angeles and Orange counties from 1990 to 1993. We find that a switching-regime model is a good predictor of hospital prices, with a hospital's bargaining power decreasing in the HMO's ability to construct an alternative network that excludes that hospital. We also find that product and geographic differentiation, as well as the plan's original network configuration, are important determinants of price. Our results show that, even in an urban area such as Los Angeles with a high hospital density, there is enough differentiation among hospitals to allow for some exercise of market power. This suggests that hospital competition may be quite localized, with defined markets much smaller than the county or metropolitan area suggested in much of the previous literature. Thus, all hospitals are not competitively equal: when competing for place in a plan's network, some hospitals can leverage their importance into higher prices.

We further investigate the antitrust implications of our parameter estimates by simulating the price effects of hypothetical hospital mergers. We find that, while most of those hypothetical mergers lead to limited price increases (less than 5%), some mergers have a much larger price effect, despite the existence of many other nearby hospitals. From a policy perspective, this suggests that while many hospital mergers may raise no significant antitrust concerns, even in urban settings, certain hospital mergers have the potential to cause real competitive harm.

While the empirical focus in this paper is on hospitals and HMOs, our modeling of the competitive environment has implications for other parts of the health care industry as well. Managed care plans also selectively contract with most types of health care providers, including physicians, dentists, optometrists, and pharmacies. Similarly, through the creation of drug formularies, managed care plans often create a network of "preferred" prescription drugs available to their enrollees.

The rest of this paper is organized as follows. Section 2 discusses the conceptual framework guiding our empirical methodology. Section 3 develops the empirical methodology, while Section 4 discusses the data on which we relied. Section 5 presents the results of our estimation, and Section 6 offers our conclusions.

[5] Feldman et al. (1990a) and Melnick et al. (1992) are the only papers we are aware of that use actual payments.

2. Price competition in an HMO network

Consider an HMO seeking to renew its contracts with the hospitals in its network, where the objective of the hospitals and the HMO is to maximize their respective profits stemming from that contract. [6] Both the hospitals and the HMO recognize that not all hospitals are equally attractive to individuals. Thus, when selecting hospitals for its network, an HMO assesses each hospital's price, appeal to enrollees, facility/service offerings, and geographic location. We assume that both the hospitals and the HMO know the profitability of different networks and the cost structures of all hospitals. [7]

A hospital's bargaining leverage with an HMO depends on the HMO's alternatives to contracting with that hospital: the less profitable those alternatives, the greater the hospital's bargaining power and the higher the price it can set. In general, HMOs cannot realistically consider every possible alternative network permutation when evaluating bids. Reconfigurations of an incumbent network require a hospital to negotiate new contracts, establishing utilization review, billing, and other HMO-specific infrastructures within newly added hospitals, and alter the admitting patterns of physicians affiliated with the HMO. Furthermore, changing the hospitals in a network can take a great deal of time and be disruptive to members, especially if the change in the hospital also necessitates a change in the physician network (Feldman et al. (1990b). For these reasons, HMOs are unlikely to radically reconfigure their hospital networks when faced with a large proposed price increase from a given hospital. Accordingly, we assume than an HMO considers only two alternative contracting actions with regard to each hospital in its network: either drop the hospital from the network, or replace it with its next best substitute hospital from outside the network.

In general, HMO enrollees face the same out-of-pocket price regardless of which network hospital they use. Thus, once a hospital is included in a network, we assume the number of patients it treats is largely unaffected by the price it or the other network members charge the HMO. While HMOs may be able to steer some enrollees to preferred hospitals, the key assumption here is that, conditional upon a hospital's inclusion in a network, the number of patients treated by that hospital is relatively insensitive to the negotiated price.

From the HMO's perspective, hospital differentiation manifests itself through the revenue differentials that the HMO earns from adding or dropping hospitals from its network. That is, a hospital's value to an HMO depends on how that hospital affects the value of the hospital network offered to potential enrollees.

Before discussing hospitals' pricing strategies, we first develop some notation. We use upper-case letters to index networks and lower-case letters to index hospitals. Let π_N denote the HMO's profits when it employs hospital network *N*. Denote the set of hospitals that form the incumbent network as N_{I}, while the term $N_{\mathrm{I}} - h$ then denotes the network created by dropping hospital *h* from network N_{I}. Similarly, $N_{\mathrm{I}} - h + m_h$ denotes the network that is

[6] Gal-Or (1997) has formulated a simple, two-hospital model in which the premium the managed care plan charges enrollees is endogenously determined when the plan formulates its network. Another related paper is Brooks et al. (1997), who estimate the parameters from a bargaining model (essentially a labor negotiations model) using hospital appendectomy pricing data.

[7] Kralewski et al. (1991) claim "the HMO knows as much (and often more) about the target hospital's cost structure as the hospital's management."

assembled by dropping hospital h and replacing it with the marginally excluded, or the next best substitute outside the network, hospital m_h. The next best substitute hospital is defined as the hospital that would generate the largest incremental profits for the HMO, assuming that the hospital priced its services at marginal cost.

A hospital's price will depend on its bargaining leverage vis-à-vis the HMO, with that leverage in turn dependent on the relative profitability of the HMO's alternative networks, $N_{\mathrm{I}} - h$ and $N_{\mathrm{I}} - h + m_h$. However, only one of these alternative networks will be the constraining influence on the hospital's price. Thus, hospital h's price will be increasing in its bargaining leverage with the HMO, where the bargaining leverage, B_h, is determined as follows:

$$B_h = \min\{\pi_{N_{\mathrm{I}}} - \pi_{N_{\mathrm{I}}-h}, \pi_{N_{\mathrm{I}}} - \pi_{N_{\mathrm{I}}-h+m_h}\} \tag{1}$$

Hospital h's bargaining leverage decreases in the ability of the HMO to turn to alternative networks that do not include that hospital. In (1), the more important a hospital is to HMO revenues, the greater the hospital's bargaining leverage (or, equivalently, the higher the HMO's opportunity cost of dropping the hospital from its network), and thus the higher the resultant negotiated hospital price.

Eq. (1) forms the basis of our empirical approach. In the next section we describe our methodology for estimating a hospital's bargaining leverage. But before turning to that empirical framework, we first discuss the assumptions underlying our conceptual framework. Specifically, we do not fully describe the network formation equilibrium, as we have not attempted to formally model the hospital network formation game when there are multiple HMOs and heterogeneous hospitals. That is a difficult task and beyond the scope of this paper.[8] Also, while we think our framework is very general and compatible with different models of HMO competition, it implicitly assumes that hospital prices in one network are not influenced by the network configuration decisions of other HMOs or of other hospital characteristics.[9] In our empirical specification we attempt to account for these effects by controlling for different hospital characteristics.

3. The empirical framework

3.1. Formulating measures of hospital substitutability

Our empirical strategy is to measure HMO enrollees' expected consumer surplus from alternative hospital networks and then use these measures as explanatory variables in a pricing regression. Since we do not have direct information about enrollees' preferences for hospitals, we cannot measure the value enrollees place on having access to different network configurations. Instead we estimate enrollees' valuation of having access to different hospitals within a given network by estimating the parameters of a utility function for inpatient hospital services.

[8] One of the difficulties a researcher would face in studying this model is the likelihood of multiple equilibria.

[9] The framework is general in the sense that both the hospital and the HMO can earn rents. The division of those rents across parties will depend on the specifics of HMO competition.

The initial step is estimating HMO enrollees' preferences across hospitals. We assume the demand for hospital care by HMO enrollees is derived from a standard discrete choice model of consumer behavior (McFadden, 1973). We assume that patients choose the hospital that maximizes their utility given their own characteristics and the characteristics of the hospitals in their feasible choice set. McFadden (1981) shows that multinomial logit can be derived from a model of utility maximization; thus the parameter estimates from the multinomial logit can be interpreted as parameter estimates of the indirect utility function.

We follow the work of Luft et al. (1990) and Burns and Wholey (1992) in which individuals' preferences across hospitals are a function of distance to hospital, quality of hospital, and other characteristics of both the hospital and the patient. To capture the influence of these variables on hospital choice, we parameterize the indirect, random utility of a patient i in the following way:

$$u_{ih}^{\mathrm{DGR}} = \xi_h + \phi_1 d_{ih} + \phi_2 d_{ih} \times \mathrm{teach}_h + \phi_3\, \mathrm{emerg}_i \times d_{ih} + \phi_4\, \mathrm{close}_{ih} + \phi_5\, \mathrm{close}_{ih} \times \mathrm{emerg}_i + \sum_{r \in R} \phi_r\, \mathrm{race}_i(r) \times \%\mathrm{race}_h(r) + \nu_{ih} \quad (2)$$

where u_{ih}^{DRG} is patient i's indirect utility from being admitted to hospital h, and this utility is assumed to be a function of the primary Diagnostic Related Group (DRG), d_{ih} the distance (straight-line) from the individual's home to the hospital h, teach_h the dummy variable indicating if the hospital is a teaching institution, emerg_i the dummy variable indicating whether the admission occurred via the emergency room, close_{ih} the dummy variable indicating whether the hospital is the closest one to the patient's home, and ξ_h the measure of relative attractiveness of the hospital, which is assumed to be common across individuals.[10]

To test whether the ethnic component of a hospital's census affects the attractiveness of the hospital to patients of different races, we include a dummy variable, $\mathrm{race}_i(r)$, which takes on the value of 1 if individual i's race is r. The variable r denotes one of four ethnic categories: Caucasian, African–American, Hispanic, and Asian. The ethnic composition of a hospital is captured by $\%\mathrm{race}_h(r)$, which measures the percentage of a hospital's inpatient population that comprises ethnic group r. The ξ's and the ϕ's are parameters to be estimated, and ν_{ih} is an i.i.d. error term that is assumed to be distributed Type I extreme value.

In this specification the perceived quality (or desirability) of the hospital will be captured by the hospital fixed effect, embodying both observable hospital characteristics such as size and unobservable (to the researcher) characteristics, such as reputation. Distance affects patient choice nonlinearly through the variables d and close. We allow the teaching status of the hospital to affect the willingness of patients to travel; if teaching hospitals are perceived to have higher quality, the coefficient of teaching status interacted with distance should be positive. Our specification also allows for patients who are to be admitted via the emergency room to be less willing to travel.

We estimate the parameters from (2) for four different samples based upon the primary DRG. That is, we allow the parameters determining hospital choice to differ by severity of illness, since some hospitals may specialize in the treatment of more severe conditions that

[10] The parameters in (2) will only be identified up to a normalization. We normalize the parameters setting $\xi_1 = 0$ for Alhambra Community Hospital.

may confer them greater bargaining power if patients place greater value on the successful treatment of these severe conditions. Let w_i^{DRG} denote the relative DRG weight as used by the federal government to determine relative Medicare payments for different DRGs. An increasing w_i^{DRG} signifies a diagnosis with a larger Medicare payment and, thus, is presumably a more complex diagnosis to treat. The classifications are: Group 1 ($w_i^{\mathrm{DRG}} \geq 2.0$), Group 2 ($1.27 \leq w_i^{\mathrm{DRG}} < 2.0$), Group 3 ($0.91 \leq w_i^{\mathrm{DRG}} < 1.27$), and Group 4 ($w_i^{\mathrm{DRG}} < 0.0.91$). Thus, Group 1 is the most severe category and Group 4 encompasses those patients with the least severe diagnoses. The category cutoffs correspond to the 85, 60, and 40th percentiles of the DRG weight distribution in our sample, respectively.

We assume that the random component of utility affecting hospital choice is Type I extreme value. This is the standard logit assumption that imposes an independence of irrelevant alternatives (IIA) substitution pattern on an individual patient's choice of hospital. The sensitivity of the welfare calculations to the logit assumption will depend upon the correlation and variance across patients in their assessments of hospital desirability. In particular, if ν_{ih} is correlated across hospitals and if the variance of ν_{ih} is large relative to the variance of ξ_h, then we are likely to formulate biased measures of welfare. However, if the model predicts well, then it is less likely that the logit assumption will be important. It turns out that we have substantial variation in the explanatory variables across individuals for a given hospital and, as we discuss below, this variation explains a significant component of hospital choice. Thus, the importance of the logit assumption is likely to be mitigated.

Although ideally the parameters of (2) should be estimated across HMO enrollees, our data do not permit that approach. This is because the patients in our patient-level data are covered by different HMOs, each of which has chosen a different hospital network determining its enrollees' hospital choice set. Without knowing that choice set for each HMO patient in our dataset, we cannot calculated unbiased estimates for (2). We address this problem by estimating (2) using the hospital selection decisions of traditional Medicare enrollees. That is, we use the Medicare population's valuations of hospitals, which we can estimate, as a proxy for HMO enrollees' valuations. We choose the Medicare population to construct this proxy because the price they pay for inpatient services (essentially a small deductible) normally does not differ by hospital, and Medicare enrollees are free to choose any hospital.[11] To mitigate the potential differences between the Medicare and HMO enrollee populations, we restrict our sample to Medicare enrollees between the ages of 65 and 70. We then assume that the parameter estimates of (2) based on the Medicare population provide an acceptable proxy for HMO enrollees' preferences. As discussed below, we test the reasonableness of this assumption by assessing how well our Medicare-based choice model describes hospital choices for a younger patient population, Medicaid enrollees.[12] While Medicaid enrollees' preferences also likely differ from those of other patients, we nevertheless find that the Medicare-based choice model translates quite well to the younger, Medicaid population, thus providing some validation of our approach.

[11] Alternatively, we could estimate the model using indemnity patients. Deductibles for indemnity plans, however, vary considerably both within, and across, insurers, thus creating price differentials across hospitals for indemnity patients. Yet, because the data include no information about deductibles, we could not control for those price differentials.

[12] Medicaid provides hospital care for low-income individuals.

Given the estimated parameters from (2), we compute estimates of the degree of substitutability of alternative networks $N_{\mathrm{I}}-h$ and $N_{\mathrm{I}}-h+m_h$. More precisely, let $W_{N_{\mathrm{I}}-h}$ denote the mean expected welfare to potential enrollees of the alternative network created either by simply dropping hospital h from N_{I}. Similarly, let $W_{N_{\mathrm{I}}-h+m_h}$ denote the mean expected welfare to potential enrollees of the alternative network created either by replacing hospital h with its next best alternative outside of the current network.

Using the DRG weights to weight utility, the formulas for $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$ are

$$W_{N_{\mathrm{I}}-h}=\frac{1}{n}\sum_{i\in E}\ln\left(\sum_{j\in N_{\mathrm{I}}-h}\exp(w_i^{\mathrm{DRG}}\hat{u}_{ij}^{\mathrm{DRG}})\right),$$
$$W_{N_{\mathrm{I}}-h+m_h}=\frac{1}{n}\sum_{i\in E}\ln\left(\sum_{j\in N_{\mathrm{I}}-h+m_h}\exp(w_i^{\mathrm{DRG}}\hat{u}_{ij}^{\mathrm{DRG}})\right) \tag{3}$$

where $\hat{u}_{ir}^{\mathrm{DRG}}$ is the expected utility of individual i, conditional on the parameter estimates of (2), of being admitted to hospital r, E the set of HMO enrollees, n the number of HMO enrollees (i.e. the number of elements in E), and w_i^{DRG} the Medicare DRG weight, where the DRG is determined from information contained in the patient discharge database (McFadden, 1981).

Hospital m_h, the next best substitute to hospital h outside of the existing network, is chosen using the following methodology. We select the n_h individuals most likely to choose hospital h, where n_h is the expected number of admissions to hospital h. Hospital m_h is the one that would garner the largest expected market share of n_h if patients' choice set was restricted to non-network hospitals.[13] In the welfare calculations, we weight expected utility by the DRG weight in order to capture the notion that the hospital choice of the more severely ill likely has larger welfare ramifications relative to those patients with minor conditions.[14]

The variables $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$ measure the relative substitutability of a given hospital within an HMO network, and should be inversely related to hospital h's bargaining leverage. That is, a hospital with a relatively high $W_{N_{\mathrm{I}}-h}$ will have little bargaining power, as it can easily be replaced. Unlike other measures of market power (e.g. the traditionally calculated Herfindahl–Hirschman Index), $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$ are hospital-specific measures of bargaining power, and since they are functions of estimated utilities, they explicitly account for the relative desirability of the hospital and the disutility of traveling. Because $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$ are based upon individuals' hospital preferences, these measures

[13] If hospitals h and m_h are under common ownership, the hospital's bargaining leverage would be greater than predicted by our model. We investigated this possibility and found that, for our HMOs, m_h and h were never under common ownership.

[14] The weighting mechanism used here, the DRG weights, is somewhat arbitrary in McFadden's welfare formation, but serves to capture differences in the importance of hospital choice associated with different diagnoses. While there are other weighting mechanisms one could use, this measure should better capture differences conditional on enrolling in an HMO compared to other possible weighting candidates (e.g. median income). As we discuss below, there is little difference in the parameter estimates of the hospital choice problem across the different severity groupings, and thus the choice of weights ultimately does not affect our conclusions.

of bargaining power do not suffer from the biases that potentially plague more traditional measures of market competition.[15]

To calculate $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$, we draw a random sample of individuals who were enrolled in any HMO and were discharged from a hospital in Los Angeles, Orange or adjacent counties. This is the appropriate population from which to calculate $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$ since it explicitly accounts for both the relative HMO populations of a given geographic area and the relative likelihood that an HMO enrollee in a given area would be admitted to the hospital.

An important assumption we make is that, conditional on the observable characteristics of hospitals, $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$ are positively correlated with $\pi_{N_{\mathrm{I}}-h}$ and $\pi_{N_{\mathrm{I}}-h+m_h}$, respectively. There are two types of scenarios in which this assumption would be invalid. First, the assumption matters if the HMO-specific costs of switching differ dramatically and unobservably across hospitals. For example, if a significant percentage of physicians in an HMO's network could not alter their admitting patterns if the hospital network were altered, then the correlation between our measure of substitutability and actual substitutability would be significantly reduced. It is difficult to test whether HMO-specific switching costs vary in important ways across hospitals, although we have found little evidence to support this possibility. The second scenario involves a severe disconnect between potential enrollee preferences over hospital networks and the ability of the HMO to market its plan because of agency/information problems. For example, if employers, who pay the bulk of insurance costs, do not place significant weight on their employees' preferences over hospital networks when considering which health insurance plans to offer, then the relationship between our welfare measures and the opportunity cost to an HMO of replacing a hospital may not hold. Some recent work suggests that HMO enrollees are admitted to higher-quality hospitals than non-HMO patients, implying that HMOs are not biasing their hospital networks towards including hospitals that enrollees do not value.[16]

3.2. *Hospital substitutability and hospital pricing*

In this section, we discuss our methods for examining the empirical relationships between hospital prices and hospital differentiation in a network environment. Eq. (1) suggests that a hospital's price will depend on how readily an HMO can switch to one of its two alternative networks that exclude hospital h. The actual network constraining price is unobservable to us. Because only one of those alternative networks (the preferred network) determines hospital h's bargaining leverage, we estimate this effect using a switching regression framework. In this framework, the regime switches according to which of the two alternative hospital networks is the constraining network.

Specifically, we write the empirical pricing relationship as

$$\ln p_{hN_{\mathrm{I}}} = X_h'\beta + (1-\alpha_h)\delta_1 \ln W_{N_{\mathrm{I}}-h} + \alpha_h\delta_2 \ln W_{N_{\mathrm{I}}-h+m_h} + \varepsilon_{hN_{\mathrm{I}}} \tag{4}$$

where $p_{hN_{\mathrm{I}}}$ is the price charged by hospital h in network N_{I}, and X_h the vector of hospital-specific variables, we discuss below that potentially affect price.

[15] See Kessler and McClellan (2000) for a discussion of the potential bias of HHI calculations.

[16] See, for example, Chernew et al. (1998).

The regression error, $\varepsilon_{hN_\mathrm{I}}$, is distributed $N(0, \sigma^2_{N_\mathrm{I}})$. The state of the system, $\alpha_h \in \{0, 1\}$, determines whether network $N_\mathrm{I} - h$ (if $\alpha_h = 0$) or $N_\mathrm{I} - h + m_h$ (if $\alpha_h = 1$) is constraining price. That state, α_h, must be inferred from the data. The unconditional probability that network $N_\mathrm{I} - h + m_h$ is constraining is defined as $Pr(\alpha_h = 1) = \lambda$. According to the framework presented in the previous section, we expect the estimated δ's to be negative. This is because $W_{N_\mathrm{I}-h}$ and $W_{N_\mathrm{I}-h+m_h}$ should be correlated with $\pi_{N_\mathrm{I}-h}$ or $\pi_{N_\mathrm{I}-h+m_h}$, and according to (1) the bargaining leverage of a hospital is decreasing in $\pi_{N_\mathrm{I}-h}$ or $\pi_{N_\mathrm{I}-h+m_h}$.

We estimate the parameters in (4) using the *E–M* algorithm in a maximum likelihood framework (Kiefer, 1980).[17] As a by-product of the estimation, the *E–M* algorithm yields inferences on $Pr(\alpha_h = 1|p, x, W_{N_\mathrm{I}-h}, W_{N_\mathrm{I}-h+m_h}; \beta, \delta)$. According to our conceptual framework, the probability that network $N_\mathrm{I} - h + m_h$ constrains price depends on the relative magnitudes of $W_{N_\mathrm{I}-h}$ and $W_{N_\mathrm{I}-h+m_h}$. The *E–M* algorithm does not constrain $Pr(\alpha_h = 1|p, x, W_{N_I-h}, W_{N_\mathrm{I}-h+m_h}; \beta, \delta)$ to follow a particular pattern; thus, we can test the hypotheses by regressing the estimated values of $Pr(\alpha_h = 1|p, x, W_{N_\mathrm{I}-h}, W_{N_{\mathrm{I}-h+m_h}}; \beta, \delta)$ on $W_{N_\mathrm{I}-h}$ and $W_{N_\mathrm{I}-h+m_h}$.

We chose the variables in X_h to capture features of the hospital environment that are not directly modeled in (1) or in the hospital choice model, but that potentially affecprices. For example, hospitals differ in their efficiency, and these differences should be accounted for in the empirical analysis. To control for these differences, we include average per diem cost in the regression. HMOs that can direct more patients to a given hospital may be able to negotiate further discounts based on that volume. This suggests the inclusion of the total number of HMO-specific inpatient days in X_h. It has also been recognized that not-for-profit hospitals may have different incentives to profit-maximize (or cost-minimize), and these potential differences could affect prices. Thus, we include dummies for-profit status. Hospitals also differ with respect to quality and higher quality hospitals may attract a sicker patient population. We attempt to control for differences in the severity of the patient population by including a case-mix index to the list of regressors. Finally, the opportunity cost of not contracting with a hospital may differ across hospitals as they may already have multiple managed care contracts. In order to control for these differences across hospitals, we include a dummy variable indicating whether a hospital's occupancy rate is greater than 85%. Hospitals with little excess capacity are likely to have a higher reservation price and, thus, to find themselves in a better bargaining position with an HMO. In our analysis, all the continuous variables are transformed by the natural logarithm.

If the prices we observe are not fully risk-adjusted, the error term in (4) may be correlated with $W_{N_\mathrm{I}-h}$ and $W_{N_\mathrm{I}-h+m_h}$. In that case, our parameter estimates would be biased. The correlation might arise if attractive hospitals attract a sicker, and therefore, more costly, patient population. We instrument for $W_{N_\mathrm{I}-h}$ and $W_{N_\mathrm{I}-h+m_h}$ by calculating $W_{N_\mathrm{I}-h}$ and $W_{N_\mathrm{I}-h+m_h}$ using estimates from (2) without hospital-specific intercepts. These new $W_{N_\mathrm{I}-h}$ and $W_{N_\mathrm{I}-h+m_h}$ variables out to prove good instruments since they should be correlated with $W_{N_\mathrm{I}-h}$ and $W_{N_\mathrm{I}-h+m_h}$ yet uncorrelated with the error term because, under our hypothesis, the instruments would not be correlated with the quality of the hospital. We can then perform a Hausman test to determine if there is any significant difference between the OLS and IV coefficient estimates.

[17] A classic application of the *E–M* algorithm in a switching regression framework is Porter (1983).

4. The data

We draw on three primary data sources: two large network-model HMOs in southern California and the Office of Statewide Health Planning and Development (OSHPD) for California. The HMOs' willingness to provide their financial data was crucial since actual contract prices negotiated between HMOs and hospitals are not publicly available. [18] The HMO data contain information about the composition of each HMO's hospital network, total inpatient payments by the HMO to each hospital, and the number of admissions and patient-days at each hospital. From this, we calculated average per diem prices paid to each hospital in the HMO's network. In general, we did not have enough information to formulate a price for the identical bundle of services across all hospitals; thus our price measure may reflect different case severities across hospitals in the network. However, we try to minimize that problem by controlling for observable severity differences across the network hospitals.

We limit our analysis to the contiguous California counties of Los Angeles and Orange, a large urban area with a population of over 11 million. The two HMOs, which we label Alpha and Beta, provided data over slightly different time periods: Alpha provided data from 1990 to 1992, while Beta provided data from 1992 to 1993. Because Alpha's revenue data were provided to us as a percentage of its total hospital expenditures, we can only construct a normalized price for a hospital in Alpha's network, with Alpha's prices normalized so that the average hospital (before dropping any observations) has a price of 100.

Summary statistics regarding the data are shown in Table 1. The average length of stay for the HMO patients in the network hospitals is not much different from the average length of stay for all HMO patients across all southern California hospitals. This suggests that there is nothing unique about the two HMOs we study here. Over the time period, we considered, Alpha's network averaged 51 hospitals, Beta's network averaged 34 hospitals, and there was very little entry or exit of hospitals from the networks. Alpha added two and dropped one hospital from its network, while Beta added four and dropped two hospitals from its network. This network stability increases our comfort in assuming HMOs make only incremental changes to their networks.

For both HMOs, the spread of average per diem prices at hospitals is large, with outliers at both tails of the distributions. [19] For example, for Beta, the median is US$ 850 and the mean is US$ 915, with a minimum per diem price of US$ 84 and a maximum of US$ 3602. Clearly, these extreme outliers cannot be accurate representations of the actual price, and may instead reflect coding mistakes or carve-out payments made to hospitals for complex procedures. To mitigate the possibility that these outliers drive our regression results, we

[18] The data were provided under the condition that we hold confidential the identity of the HMOs and the hospitals.

[19] The large variance in price across hospitals is surprising and raises the possibility that our price data may contain significant errors. As described below, we tested the data in several ways to see if the price variance reflects systematic biases that may confound the analysis. Furthermore, the distribution of prices we observe in our data is similar to the distribution of other hospital pricing data in which the actual prices are perfectly observed. We have hospital pricing data for a New York state HMO in which we observe (without error) the actual prices paid by the HMO to hospitals. The pricing data there displays a similarly high variance. Thus, in this case, the observation that the pricing data has a high variance does not necessarily imply that there are significant errors in the data.

Table 1
Summary statistics of hospital variables (standard deviations in parentheses)[a]

Variable	Entire hospital population	HMO Alpha network hospitals	HMO Beta network hospitals
Number of hospitals per year (mean number of hospitals per year prior to trimming)	109	44.5 (51)	30 (34)
W_{N-h}	–	35.17 (0.93)	24.86 (0.96)
W_{N-h+m_h}	–	37.18 (0.99)	26.64 (1.11)
HMO admissions	–	110.6 (78.7)	161.7 (128.4)
Mean price (US$)	–	97.8 (60.1)	871.2 (363.4)
$\hat{\xi}_h$	0.76 (0.98)	1.01 (0.93)	0.90 (1.01)
Licensed beds	243.1 (191.3)	293.4 (202.7)	281.6 (164.9)
Percent non-profit (%)	55	71	48
Percent for-profit (%)	42	27	48
Mean length of stay for HMO patients (entire hospital census/HMO-specific)	3.89 (1.49)	3.83 (1.31)	3.92 (1.54)
Costs per day (US$)	881 (251)	879 (221)	861 (199)
Occupancy rate	0.57 (0.19)	0.61 (0.19)	0.56 (0.17)
Mean HHI	0.063 (0.076)	0.069 (0.086)	0.054 (0.059)

[a] Network hospitals are those that signed a contract and admitted at least 10 HMO patients in a year. "Inpatient Days" refers to the number of inpatient days each HMO enrollee spends on average at the hospital. "Mean length of stay for HMO patients" is measured using the entire inpatient population for the whole sample, but is HMO-specific for HMOs Alpha and Beta; $\hat{\xi}_h$ is the estimated hospital-specific intercepts from the hospital choice estimation for the Group 1 Severity sample, respectively. "Costs per day" are measured using the entire inpatient population of the hospital.

trim our data according to the following rules.[20] For Alpha, we dropped a hospital for that year if its normalized price was less than 50 and greater than 330. For Beta, we dropped a hospital observation for that year if its per diem price was less than US$ 400 and greater than US$ 1500. This reduced Alpha's sample by nine observations (leaving a total of 89 observations) and Beta's sample by nine observations (leaving a total of 90 observations). In general, the high-priced hospitals were larger ones (mean bed size = 564) and the low-priced hospitals were significantly smaller than average (mean bed size = 110). We experimented with different cut-off rules, and the qualitative implications of the results were remarkably consistent across the different rules.[21]

We explored whether these price variations reflect differentials in severity of patient mix. Some hospitals in Alpha's network were paid on a DRG basis, and we have actual payment information for those hospitals for 1993. Thus, we compared the distributions of the payments within a DRG category across hospitals to the average prices paid across all DRGs for those hospitals. We focus on DRG 373 (normal obstetric deliveries without complications), as there are many admissions in this DRG and severity differentials across hospitals is likely smaller for this DRG than for many other DRGs. Of the 32 hospitals paid on a DRG basis, the average normalized payment is 94 with a standard deviation of 17

[20] The calculation of the measures of hospital substitutability was based on the entire network of hospitals prior to any trimming of the sample.

[21] One hospital had an average per diem cost less than US$ 200; we also dropped that hospital from our sample. Our qualitative results were unaffected, though, even when we did no trimming at all.

and a range of 91. Thus, even within this DRG, there is substantial price variation across hospitals. Furthermore, the prices paid in this DRG are significantly correlated ($\rho = 0.40$) with average total price paid to the hospital across all DRGs. This suggests that any bias in our own price measure due to differences in patient severity ought to be limited, especially given our effort to control for severity differences by adding a severity measure in our regressions.

There is substantial overlap in hospitals across the two networks: 24 hospitals are members of both HMO networks. The correlation of prices across hospitals that are common to both networks can yield some information about the nature of the price data. In particular, a high correlation suggests either that the price data do not reflect differential severity or that the severity differences across hospitals are similar for both HMOs. If the price data do not reflect differential severity, then our price variable is measuring what we would like it to measure. However, if the latter case is true, we should be able to control for severity differences across hospitals using aggregate hospital severity indexes, which suggest (although the evidence is not definitive) that the differences in severity across hospitals for a given HMO reflect general differences in severity across hospitals for other payers.

The Spearman rank correlation of price across the two HMO networks for these 24 hospitals is 0.54. This strikes us as a reasonably high correlation, suggesting that our estimation methodology will not be susceptible to biases caused by errors in our price variable.

Hospital-level data were provided by California's Office of Statewide Health Planning and Development (OSHPD). That dataset included information such as hospital average per diem costs, affiliations, teaching status and for-profit status. Our data also include the longitude and latitude for the center of each zip-code that was obtained from the TIGER database.[22] These longitude/latitude data allow us to calculate straight-line distances using the Great Circle formula between hospitals and patients' home zip codes.[23]

To estimate the hospital choice problem and obtain parameter estimates for (2), we also used OSHPD's 1992 patient discharge data. This patient-level dataset provides information on every individual hospitalized in California, including information about their zip-code of residence, primary DRG, race, sex, age (by classes), admitting hospital, source of admission (emergency room, etc.), expected source of payment, and disposition (normal discharge, death, etc.). We then limited those data to include only patients admitted to a hospital in Los Angeles and Orange counties.[24]

We used OSHPD's principal source of payment field to determine whether a patient was a Medicare, HMO, or Medicaid enrollee. For purposes of estimating patients' preferences across hospitals, we first divided the Medicare population into four samples based upon complexity of care as proxied by their DRG. We then removed from the dataset any patient who was transferred from another acute-care hospital we well as those patients with missing

[22] Center-of-zip-code longitudes and latitudes can introduce significant error when zip codes are very large. By restricting our study to hospitals in the Los Angeles/Orange county metropolitan area, where most zip codes are relatively small, we largely avoid this problem.

[23] Using data from upstate New York, Phibbs and Luft (1995) show a strong correlation between travel times and straight-line distances. We assume the same correlation holds for the metropolitan Los Angeles region.

[24] We also estimated the model including patients from San Bernardino and Riverside counties to ensure that the estimates for hospitals near the county borders are not significantly affected by excluding hospitals in adjacent, but non-included, counties.

zip-code information or who were admitted to Kaiser hospitals. We next took a random sample of approximately 8000 Medicare enrollees between the ages of 65 and 70 for each severity sample. Hospitals that had less than 50 total Group 1 admissions were dropped from all severity samples. To calculate $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$ we drew a random sample of approximately 12,700 HMO enrollees from the OSHPD hospital discharge dataset.

5. Results

5.1. Hospital choice and measures of hospital substitutability

We first estimate the parameters from (2) using multinomial logit and the Medicare enrollee data. In general, individuals did not travel far to receive care, although the more severely ill population traveled slightly farther than their less acute counterparts. The average distance traveled for patients in Group 1 was 12.6 km versus 10.5 km for Group 4.

Table 2 presents the results of the multinomial logit estimates of (2). The parameter estimates all have the expected sign. Patients are more likely to go to closer hospitals (with

Table 2
Parameter estimates from multinomial logit hospital choice model with hospital fixed effects (standard errors in parenthesis)

Variable	Group 1 severity sample (high severity)	Group 2 severity sample	Group 3 eseverity sample	Group 4 severity sample (low severity)
Distance	−0.120 (0.004)	−0.137 (0.003)	−0.156 (0.002)	−0.146 (0.004)
Teaching × distance	0.030 (0.002)	0.035 (0.001)	0.037 (0.002)	0.020 (0.003)
Emergency × distance	−0.049 (0.002)	−0.003 (0.001)	−0.005 (0.002)	−0.002 (0.002)
Closest	1.27 (0.05)	1.25 (0.04)	1.14 (0.09)	1.26 (0.06)
Closest × emergency	1.18 (0.19)	0.43 (0.18)	0.27 (0.08)	0.48 (0.15)
Caucasian × %Caucasian admissions	2.33 (0.16)	3.05 (0.15)	2.25 (0.13)	2.30 (0.20)
African–American × %African–American admissions	3.48 (0.43)	3.54 (0.45)	4.51 (0.56)	4.31 (0.25)
Hispanic × %Hispanic admissions	1.99 (0.44)	1.85 (0.45)	2.22 (0.39)	2.17 (0.47)
Asian × %Asian admissions	5.72 (1.31)	5.32 (1.10)	6.59 (0.94)	5.74 (1.43)
Mean ξ_h	0.76	1.28	0.26	0.47
Standard deviation of ξ_h (mean standard error of ξ_h)	0.98 (0.14)	1.05 (0.16)	0.90 (0.09)	0.89 (0.11)
Max ξ_h	2.64	3.12	1.87	2.24
Hospital with highest average desirability	UCLA	Cedars–Sinai	UCLA	Cedars–Sinai
Minimum ξ_h	−1.44	−1.50	−1.72	−1.81
N	7.025	6.883	7.157	7.313
Log likelihood	−20.899	−19.987	−20.323	−20.989
Mean distance traveled (in km) to admitting hospital	12.6	11.3	9.8	10.5

the closest hospital being preferred) and, in general, patients are less sensitive to distance as their severity of illness increases. Also, prospective patients are more willing to travel farther to obtain services at a teaching hospital. The estimates indicate that patients admitted via emergency room are less willing to travel long distances.

Space does not permit presenting all of the hospital-specific coefficients, ξ_h, here; however, we provide information regarding the distribution of those coefficients in Table 2. The average value of the absolute value of the *t*-statistics across the different samples is 17.2. In addition, well-known and highly regarded hospitals have estimated coefficients that are in the upper tail of the distribution. The hospital with the highest estimated coefficient for Groups 1 and 3 is UCLA hospital, while the hospital with the highest estimated coefficient for Groups 2 and 4 is Cedars–Sinai. [25] There is a high degree of correlation in the hospital intercepts across the different samples. The correlation between the Groups 1 and 4 coefficients is 0.94. Regression analysis (which we do not present here but is available from the authors upon request) shows that the estimates of ξ_h increase with bed size and are larger for not-for-profit hospitals.

Table 2 also shows how racial demographics affect hospital choices. For all four racial groups, the coefficient on the interaction of the racial dummy with the percentage of that race in the hospital is positive and significant. This is consistent with the anecdotal information that some California hospitals market themselves directly to various ethnic groups by offering specialized staffing, medical treatment, language services, and food services.

Our model explains hospital choice well. There are several possible measures of goodness of fit in discrete choice models. We examine the fit of the model by analyzing predicted versus actual hospital choice. We construct a hit-or-miss criteria where the predicted choice for a patient is the hospital having the maximum predicted probability. The model correctly predicts 31, 30, 29, and 29% of hospital choices correctly for the Group 1 through Group 4 severity samples, respectively. Given the large number of choices available to patients (109 hospitals), these prediction rates suggest the model provides a high degree of explanatory power.

The validity of our approach depends upon whether hospital preferences for Medicare patients are similar to those of HMO patients. We test this by measuring how well Medicare patients' preferences predict hospital choices of the Medicaid population. Demographically, the Medicaid population is very different from the Medicare population and, if our model can explain the Medicaid population's choices, that will suggest that our estimated parameters are also representative of the HMO population. For each severity category we examine how accurately the logit model predicts admission to a hospital.

Because Medicaid selectively contracts with hospitals, we need to determine Medicaid patients' feasible choice set. We define a Medicaid network hospital as one that treated at least 1.5% of the Medicaid patients in our OSHPD sample. Our model correctly predicts 27, 27, 23, and 24% of the hospital choices for the Medicaid Group 1 through Group 4 severity samples, respectively. These hit rates are high for multinomial logit models and are close to the hit rates for the Medicare population upon which the estimates are based. This suggests

[25] The most desirable hospital is calculated using the formula $\xi_h + \hat{\phi}_2 \times 15 \times \text{teach}_h$. If the hospital is a teaching institution, this formula calculates the desirability of the hospital for a patient who lives 15 km away.

that our parameter estimates from the Medicare population are reasonable approximations of the HMO population's parameters.

Table 1 lists the summary statistics for $W_{N_{\mathrm{I}}-h}$ and $W_{N_{\mathrm{I}}-h+m_h}$ as well as for other hospital characteristics for both HMOs. The hospitals comprising the two HMOs' networks differ somewhat from the general population of hospitals since, on average, the network hospitals are larger and more attractive to potential patients. The typical HMO hospital also appears to face substantial competition as measured by the Herfindahl–Hirschman Index (HHI), with the average HHI 0.069 for Alpha and 0.054 for Beta.[26] Only 10% of the hospitals across both HMOs were in a relatively concentrated (HHI > 0.2) environment. Interestingly, the size and composition of the two hospital networks are quite different, suggesting that the HMOs are pursuing somewhat different network strategies.

For each hospital, we identify the next closest substitute hospital outside of the current network, m_h. For Alpha, the average distance to the closest substitute hospital outside of network is 21.3 km. For Beta, the average distance to the best substitute hospital outside the network is 10.3 km. The difference in the average distance is consistent with Alpha using a larger network, thereby having fewer hospitals outside of the network from which to choose. These figures thus suggest that hospital competition is quite localized even in large urban areas with high hospital densities.

5.2. Explaining hospital prices

Columns (1) and (3) in Table 3 present the coefficient estimates of the switching-regime model in (4).[27] Consistent with the framework discussed in Section 2, hospital prices seem to be best described by the switching-regime framework. For both HMOs, the coefficients on $\ln W_{N-h}$ and $\ln W_{N-h+m_h}$ are negative and significant at the 5% level. The variables W_{N-h} and W_{N-h+m_h} measure the relative values of the network absent hospital h and are, therefore, inversely related to the value of the hospital to the network. Thus, we expect a negative coefficient on these variables. The magnitudes of the estimated coefficients indicate that a one standard deviation decrease in W_{N-h} (when W_{N-h} is the binding network) will lead to a 9.8 and 5.7% mean increase in price for hospitals in networks Alpha and Beta, respectively. For HMO Beta, this translates to a US$ 49 increase in the per diem profits of the mean priced (US$ 915) hospital. Thus, hospitals with bargaining power can seemingly leverage their importance to the HMO's network into significantly higher prices.

Our estimates indicate that, for the majority of hospitals, the binding threat held by HMOs is to drop a hospital from the network without replacing it. For Alpha, the estimate for $Pr(\alpha_h = 1)$ is 0.21. Thus, for Alpha network $N_{\mathrm{I}} - h + m_h$ constrains price 21% of the time, while $N_{\mathrm{I}} - h$ constrains price 79% of the time. For Beta, network $N_{\mathrm{I}} - h + m_h$ is the constraining network 38% of the time. This difference is consistent with the different sizes of the two HMOs' networks. As the smaller network, Beta has more hospital options

[26] We calculated the HHI using hospital beds as the measure of size and, solely for the purposes of this exercise, we approximated markets as a 15 km circle drawn about a hospital. Regressions of the HHI on the logarithm of hospital price controlling for hospital size, for-profit status, and occupancy rates did not yield significant coefficients for HHI for either HMO network.

[27] The coefficient estimates are robust to different starting values.

Table 3
Switching regression and OLS estimates of the determinants of hospital pricing dependent variable is the logarithm of price (standard errors in parentheses)[a]

Variable	HMO Alpha		HMO Beta	
	Switching regression (1)	OLS (2)	Switching regression (3)	OLS (4)
Constant	16.34 (5.75)[c]	72.61 (27.98)[c]	15.47 (3.29)[c]	24.91 (12.3)
Log of HMO inpatient days	−0.032 (0.019)	−0.12 (0.036)[c]	0.23 (0.11)[b]	0.053 (0.031)[b]
Log of HMO LOS	0.10 (0.052)[c]	0.12 (0.11)	0.17 (0.012)	0.14 (0.10)
Log of cost per patient day	0.26 (0.076)[c]	0.33 (0.14)[c]	0.11 (0.038)	0.21 (0.11)[b]
Case-mix index	0.021 (0.061)	0.24 (0.10)[b]	0.13 (0.013)[c]	0.19 (0.094)[b]
Not-for-profit (public omitted)	−0.56 (0.093)[c]	−0.53 (0.067)[c]	0.072 (0.043)[c]	0.55 (0.13)[c]
For-profit	−0.81 (0.10)[c]	−0.74 (0.10)[c]	0.15 (0.053)[c]	0.65 (0.15)[c]
Occupancy rate > 85%	−0.06 (0.053)	0.098 (0.099)	0.16 (0.071)[b]	0.30[c] (0.11)
$\ln W_{N_{\mathrm{I}}-h}$ ($\alpha_h = 0$)	−3.50 (1.58)[b]	−13.50 (4.15)[c]	−1.44 (0.69)[b]	−6.11 (2.48)[c]
$\ln W_{N_{\mathrm{I}}-h+m_h}$ ($\alpha_h = 1$)	−3.70 (1.60)[b]	−5.81 (4.12)[b]	−1.62 (0.71)[b]	−0.30 (1.76)
$Pr(w_{hn} = 1)$	0.21	–	0.39	–
R^2	0.87	0.51	0.86	0.45
Log likelihood	−37.6	–	−57.0	–
Hausman test P-value	0.17	0.70	0.96	0.22
N	89	89	90	90

[a] Annual dummies are also included in the regressions but are not reported.
[b] Significant at the 5% level.
[c] Significant at the 1% level.

outside the network than does Alpha. Similarly, hospital h constitutes a larger piece of Beta's overall network. We would expect that Beta would be more likely than Alpha to replace hospital h with another hospital than to simply drop that hospital without replacement. This is consistent with our coefficient estimates.

Importantly, other implications of the parameter estimates are sensible. An increase in the desirability of the hospital, as measured by $\hat{\xi}_h$, will result in the hospital receiving a higher per diem payment. If a hospital were to increase its desirability by 1.0 for all severity categories (approximately a one standard deviation increase), the parameter estimates indicate that its expected per diem payment would increase by 3.76% for HMO Alpha and US$ 17.64 for the mean hospital in HMO Beta's network. We can translate this effect into an expected HMO premium increase for HMO Beta.[28] The expected increase in the monthly premium induced by a single hospital increasing its desirability by a substantial 1.0 is US$ 0.27. This strikes us as a very plausible figure.

For the most part, the rest of our coefficient estimates are plausible. For Alpha, the coefficients on costs are positive and significant while the coefficient on the number of HMO inpatient days is negative and insignificant. For Beta, the coefficient on the number of HMO inpatient days is significant and positive. Interestingly, we do not find statistically

[28] The formula is: Annual increase $= (1 + m) \times (P'_{\mathrm{new}} S_{\mathrm{new}} - P'_{\mathrm{old}} S_{\mathrm{old}}) \times$ expected number of inpatient days, where m is the HMO's profit margin, P the expected per diem network price vector, S the vector of the expected, within network, hospital shares. In these calculations we assume that the margin is 10% and that the expected number of inpatient days is 0.35 per year.

significant differences between not-for-profits and for-profits when it comes to pricing behavior. While the coefficients are significant in both regressions (public hospitals are the omitted category), they are not significantly different from each other. In antitrust actions against hospital mergers involving not-for-profit institutions, a common defense is to claim that not-for-profit hospitals respond to competition differently than for-profit hospitals. This argument was successfully made by the hospitals in FTC versus Butterworth Hospital Corp. (1996).[29] Our results provide no support for the notion that for-profit and not-for-profit hospitals price differently.

For comparison purposes we also report the results from OLS regressions of the logarithm of hospital prices and hospital characteristics in Table 3. The fits under the switching regime models are much better than under OLS. The R^2 in switching regime models is 0.87 and 0.86 for Alpha and Beta, respectively. The corresponding R^2 for the OLS regressions is 0.51 and 0.45. The coefficient estimates have the same sign across the two estimation procedures.

For both HMOs, likelihood ratio tests of the null hypothesis that no switch in regimes occurs (e.g. $\alpha_h = 0$ for all observations) can be rejected at any traditional level of confidence.[30] The test statistics are 879 and 8734, and they are distributed Chi-squared with 1 d.f.

Table 3 also reports the *P*-values of the Hausman test that price contains an unobserved severity component that is correlated with W_{N-h} and W_{N-h+m_h}. We describe the hypothesis and the test in Section 3. We performed the test using both the switching regression and OLS results. The Hausman test in the switching regression context was performed by estimating (4) using IV and OLS, treating the estimated probabilities as data. In all cases, the Hausman test fails to reject the hypothesis that there are unobserved severity differences across hospitals that are correlated with W_{N-h} and W_{N-h+m_h}. This suggests that our coefficient estimates are not contaminated by biases due to unobserved severity.

The *E–M* algorithm generates estimates of $Pr(\alpha_h = 1|p, x, W_{N_I-h}, W_{N_I-h+m_h}; \beta, \delta)$ for each observation. The estimation methodology places no restrictions on the patterns that these probabilities must follow. Thus, we can test the predictions of our model by regressing the estimated $\ln(Pr(\alpha_h = 1|p, x, W_{N_I-h}, W_{N_I-h+m_h}; \beta, \delta))$ on $\ln W_{N_I-h}$ and $\ln W_{N_I-h+m_h}$. We would expect the coefficient on $\ln W_{N_I-h}$ to be negative and the coefficient on $\ln W_{N-h+m_h}$ to be positive. Table 4 presents the results of these regressions. For both HMOs the coefficient estimates conform to our expectations; the coefficients on $\ln W_{N-h}$ are negative and significant while the coefficients on $\ln W_{N-h+m_h}$ are positive and significant. Thus, the likelihood that network $N_I - h$ is the constraining network increases in the value of W_{N-h} and decreases in the value of W_{N-h+m_h}.

5.3. *The effects of hospital mergers*

In this section, we explore the antitrust implications of our parameter estimates by simulating the effects of several hypothetical hospital mergers. For both HMOs, we simulate the

[29] The January 1999 issue The Journal of Health Economics devotes several articles to this matter. Also see Vita and Sacher (2000).

[30] The test statistic is $2N(L_1 - L_0)$ where L_1 is the log likelihood under the switching regime model and L_0 is the log likelihood under the assumption that $\alpha_h = 0$ for all observations.

Table 4
OLS regression estimates of the determinants of probability $w = 1$ dependent variable is the logarithm of $Pr(w_h = 1 | p, x, W_{N_I-h}, W_{N_I-h+m_h}; \beta, \delta)$ (standard errors in parentheses)

	HMO Alpha	HMO Beta
Constant	−57.73 (83.43)	−51.13 (52.11)
$\ln W_{N-h}$	−100.25 (26.57)[a]	−53.68 (18.85)[a]
$\ln W_{N-h+m_h}$	81.16 (26.52)[a]	66.48 (17.63)[a]
R^2	0.13	0.13
N	89	90

[a] Significant at the 1% level.

two types of mergers most likely to have an anticompetitive effect: (1) a merger between a hospital and its next best substitute hospital within the network and (2) a merger between a hospital and its next best substitute hospital outside the current network. We conduct these simulations for each hospital in the HMOs' networks.

To estimate price increases, we identify a hospital's next best substitute inside the network in the same way that we identified m_h, the next best substitute hospital outside the network. Once we identify the next best substitute hospitals from among all hospitals in the metropolitan area, we assume that hospital h and its next best substitute hospital bundle their services when negotiating with the HMO. In this scenario, assuming the merger does not affect which alternative network is the constraining one, the increase in bargaining power will be given by

$$M_h = \begin{cases} (1-\alpha_h)(W_{N_I-h} - W_{N_I-h-h'}) & \text{if } h' \in N_h \\ \alpha_h (W_{N_I+m_h-h} - W_{N_I-h+h'}) & \text{if } h' \notin N_h \end{cases} \tag{5}$$

where M_h denotes the change in bargaining power due to the merger, h' the hospital that is merged with hospital h, and α_h the indicator of whether network $N_I - h$ (if $\alpha_h = 0$) or $N_I - h + m_h$ (if $\alpha_h = 1$) is constraining the hospital's price. The effect of the merger will depend on which alternative network is binding the hospital's price and whether the merged hospital is inside or outside the current hospital network.

Once we calculate the change in welfare, M_h, the expected change in price is easily calculated from the coefficients in Table 3. In this calculation, we take into account the probability that the merging hospitals do not affect the constraining network and, thus, would not affect prices. [31]

On average, the predicted post-merger price increase was modest. For Alpha, the expected price increase for a merger between a hospital and its next best substitute within the current network is 7.2%, with 59% of those mergers causing a price increase greater than 5%. The average predicted price increase for mergers between a hospital and its next best substitute outside of the current network is 1.8%, with 15% of the mergers causing a price increase greater than 5%. For Beta, the average predicted price increase for a merger between a hospital and its next best substitute within the current network is 3.2%. Of these mergers,

[31] Some caution is warranted in interpreting these findings, as they are based on paramter estimates from a reduced-form model and we are performing an out-of-sample policy experiment.

39% cause a price increase greater than 5%. The average predicted price increase for mergers between a hospital and its next best substitute outside of the current network is 2.1%. Twenty-two percent of these mergers lead to an expected price increase greater than 5%. Of the 358 mergers simulated here, a significant number (26%) lead to an expected price increase greater than 5%.

While these average price increases are not large, we find that a substantial number of mergers did lead to significant price increases. This suggests that hospital mergers, even in urban areas of considerable hospital density, can result in significant price increases.

6. Conclusion

We analyze the strategic environment in which an HMO contracts with hospitals to create a network that current and potential enrollees will find attractive. We hypothesize that a hospital's price is constrained by the degree of substitutability between an HMO's current hospital network and its next best alternative network that excludes the hospital.

We test these predictions using a unique dataset. These data include actual HMO payments by two of the largest HMOs in southern California to hospitals in Los Angeles and Orange counties. Our empirical results confirm our hypothesis: a hospital's bargaining power depends on its incremental value to a health plan's network. The hospital's incremental value is determined by the plan's opportunity cost of either replacing the hospital with another one outside of its network, or else simply dropping the hospital and marketing a smaller hospital network. This suggests a very different analytical framework for assessing hospital competition than has previously been postulated; in effect, hospital competition should be viewed as competition for a spot in a health plan's network, and the extent to which one hospital competes with another depends on which hospitals are already in the plan's network and how each hospital complements other hospitals in the plan's network.

We also find that hospital competition is characterized by significant geographic and product differentiation across hospitals. This differentiation serves to limit hospital competition, even in an area with such high hospital density as the Los Angeles region. Moreover, this differentiation creates the potential for certain hospital mergers to significantly increase hospitals' bargaining leverage. We confirm this prediction by simulating hospital mergers in the Los Angeles region, and find that a significant number of those simulated mergers lead to predicted price increases in excess of 5%. These findings indicate that, even in urban areas, certain hospital mergers can significantly increase market power.

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