RAND Journal of Economics
Vol. 34, No. 4, Winter 2003
pp. 737–763

Competition and market power in option demand markets

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We call markets in which intermediaries sell networks of suppliers to consumers who are uncertain about their needs "option demand markets." In these markets, suppliers may grant the intermediaries discounts in order to be admitted to their networks. We derive a measure of each supplier's market power within the network; the measure is based on the additional ex ante *expected utility consumers obtain from the supplier's inclusion. We empirically validate the WTP measure by considering managed care purchases of hospital services in the San Diego market. Finally, we present three applications, including an analysis of hospital mergers in San Diego.*

1. Introduction

■ Some important markets feature intermediaries that offer a network of upstream suppliers to downstream consumers. Examples include general contractors, who assemble networks of skilled craftsmen and subcontractors; business-to-business web sites, which assemble networks of parts suppliers; and managed care organizations, which assemble networks of hospitals and physicians. These intermediaries take advantage of their expertise and purchasing economies to identify superior suppliers and extract better terms than could consumers shopping on their own. In some cases, such as managed care, they also provide insurance against the risk of needing the network's services.

Sometimes, consumers may know their specific needs at the time they select their intermediary. For example, homeowners may have detailed architectural plans at the time they select their building contractors. In other situations, consumers may select their intermediary before knowing their specific needs. Insurance markets are an important example. Automobile owners often commit to a network of auto repair shops at the time they purchase collision insurance, even though they do not know in advance what kinds of repairs their cars might require. Similarly, patients

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The authors thank Steve Berry, Shane Greenstein, Richard Lindrooth, Rob Porter, and seminar participants at Harvard University, Stanford University, the University of Chicago, the 2002 CSIO/IDEI Industrial Organization Workshop held at Northwestern University, and the 2002 NBER Summer Institute's joint meeting of the Industrial Organization and Productivity Workshops.

commit to a network of medical providers at the time they purchase their health insurance, but before they know their specific medical needs. Noninsurance examples include manufacturers who sign long-term contracts with suppliers, who in turn outsource specific manufacturing tasks as the need arises. Following Dranove and White (1996), we call these ”option demand markets” (or OD markets). In OD markets, consumers commit to a potentially restricted network of sellers prior to fully knowing their needs, but retain the option to visit any seller in the network once their needs are known. The value that any one consumer places on a given network depends on his expectation of how well the network's members will be able to meet his needs. This contrasts with direct-purchase markets, in which consumers do not eliminate any potential sellers prior to learning their needs.

The article's goal is to develop and validate an index of the market power of suppliers in OD markets. We consider a competitive intermediary assembling a network of suppliers on behalf of many consumers. We assume that consumers' preferences follow the logit model of demand. We also suppose the intermediary knows the underlying logit utility function, the distribution of consumer characteristics, and the distribution of the possible states of the world that affect demand, but not the upcoming demand realizations. A straightforward calculation based on the properties of logit demand gives an estimate, for each supplier, of how much consumers in aggregate are willing to pay *ex ante* to retain it in the network.[1] A simple reduced-form bargaining model between the supplier and the intermediary suggests that a portion of this willingness-to-pay (WTP) is captured by the supplier. The WTP associated with a supplier is therefore a measure of its market power: a supplier for which WTP is high secures higher prices from the intermediary than does a supplier for which WTP is low.

After deriving the formula for WTP, we validate the measure by examining hospitals in the San Diego, California, metropolitan area. Following our discussion, managed care organizations (MCOs) in this market are the intermediaries and hospitals are the suppliers. Each MCO negotiates bilaterally with each hospital for inclusion in its network. Its goal is to come to agreement on rates with a set of hospitals such that the resulting network maximizes the difference between consumers' *ex ante* WTP for that network and its expected payments to the hospitals that provide the services. To the extent that the MCO succeeds in doing this it can offer employers a competitive price on a health plan that employees value highly. Once the network is formed, consumers realize their health state and, for those who need hospitalization, select the hospital they most prefer from among those included in their network.

Using 1991 data on inpatient hospital services in San Diego, we estimate a multinomial hospital-choice model for patients who have a free choice of hospital. This provides estimates of the parameters of patients' logit utility functions. Based on these parameter values and the empirical distributions of patient characteristics and health states we compute, for each hospital, the consumers' aggregate *ex ante* WTP to retain it in the network.[2] These WTP measures are denominated in “utils” because in estimating the logit function we intentionally select consumers who did not face prices that vary across hospitals. To convert utils to dollars, we regress each hospital's actual profits from inpatient services provided to managed care patients onto our estimates of consumers' *ex ante* WTP. The results of this regression are consistent with the validity of the WTP measure: WTP is a highly significant predictor of hospital profits.

The last section of the article offers several applications of the WTP measure. Of greatest interest, we show how to use WTP to define geographic markets under current federal merger guidelines. In this application, we estimate how much, if any, additional profit two or more hospitals are able to extract from MCOs after increasing their WTP through a merger. We then infer the effect of the merger on prices. When we conduct this exercise for a merger among three geographically close hospitals in the suburbs of San Diego, we estimate that prices would increase by more than 10%, under the assumption of zero cost changes. Under the merger guidelines, this

[1] Brandenburger and Nalebuff (1996) refer to this as “added value.”

[2] We exclude the Kaiser Health Plan hospital.

implies that the south suburbs are a well-defined geographic market. As a byproduct of this analysis, the courts could compare the predicted price increase, under the assumption of zero cost changes, against any asserted cost savings. This is essential to any rule-of-reason assessment of a proposed merger.

2. Background on antitrust

■ In the 1990s, the U.S antitrust agencies lost virtually every challenge to hospital mergers.[3] In most of the contested merger cases, the court's ruling turned on geographic market definition. To define geographic markets, the antitrust agencies recommend using the small but significant nontransitory increase in price (SSNIP) criterion.[4] Under SSNIP, a narrow trial market definition is initially proposed. If the firms in the trial market could collectively implement a SSNIP, then they constitute the relevant set of competitors. If they cannot do so, then it must be because a relevant competitor was excluded. In this case, the proposed market is expanded until the SSNIP criterion is met.

Rather than directly observing or attempting to predict price effects, the courts often rely on proxy measures. A popular proxy measure in hospital merger cases is derived from methods introduced by Elzinga and Hogarty (1973). Elzinga and Hogarty and related approaches use aggregate inflows and outflows of patients (or imports and exports of goods) to determine market boundaries. Given the propensity of some patients to travel substantial distances for care, this standard has led to large market boundaries and, consequently, permissive merger rulings.

Our results indicate that this may be a serious error. The south suburbs of San Diego would not be a well-defined market under Elzinga and Hogarty, yet the WTP approach indicates that they are. We conclude that the willingness of some patients to travel does not eliminate the market power hospitals may have in their local neighborhood. Many patients, especially those with conditions that are relatively straightforward to treat, have a strong preference to go to a convenient, nearby hospital. These preferences give hospitals with no nearby competitors a strong bargaining position.

3. Related literature

■ There is an extensive literature on hospital pricing.[5] One branch of that literature, which includes Noether (1988), Dranove, Shanley, and White (1993), Lynk (1995), and Keeler, Melnick, and Zwanziger (1999), consists of traditional price-concentration studies using average hospital prices across a large cross-section of markets. Another branch that includes Staten, Umbeck, and Dunkelberg (1988) and Melnick et al. (1992) examines the hospital prices paid by specific health insurers. Both of these branches share two difficulties that our article addresses.

First, because they use exogenous measures of market structure based on geographic delineations or aggregate patient flow analyses, all of these studies fail to account for rich differentiation and substitution patterns across individual sellers. They ignore the fact that hospital competition in a metropolitan area is fought out in thousands of micro markets—each neighborhood and each diagnosis is a distinct micro market. Our WTP measure of market power respects this fine structure by using a parsimonious, theoretically justified formula for approximating patients' WTPs in each micro market and then adding them up to obtain an aggregate measure.

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[3] Losses include Poplar Bluff, Missouri (*FTC* v. *Tenet Healthcare Corp*., E.D. MO 1998, reversed 8th Cir. July 1999); Joplin, Missouri (*FTC* v. *Freeman Hospital*, W.D. MO 1995); Long Island, New York (*United States* v. *Long Island Jewish Medical Center*, E.D. NY 1997); and Dubuque, Iowa (*United States* v. *Mercy Health Services*, N.D. Iowa 1995). See Capps et al. (2002) for a more detailed discussion of these cases.

[4] The benchmarks are a 5% price increase and a one-year duration.

[5] Our article also relates to the literature on common agency. In this literature, several principals contract with a single agent who exerts effort to sell the principals' services. In our setting, hospitals (the principals) contract with an intermediary (the agent) who sells the option to use the hospitals' services to consumers, usually through their employers. The common-agency literature generally assumes that the agent has imperfect information about the attributes of the principals (e.g., their costs) and studies both the principals' noncooperative negotiation strategies and the agent's incentives to exert effort. See, for example, Bernheim and Whinston (1985, 1986).

Second, prior work on hospital pricing has been based on an analogy with conventional markets in which individual consumers make their purchase at the time they know their needs. This is inappropriate for hospital services. With the prevalence of managed care, almost all consumers select among alternative bundles of providers not at the *ex post* stage, but at the *ex ante* stage before they know their diagnoses. The proper theoretical construct for measuring market power in such an option demand market must therefore be based on some form of *ex ante* expected willingness-to-pay aggregated over all consumers. The main contribution of this article is to show how to construct such a measure from first principles and to provide preliminary empirical evidence that it is in fact a useful construct.

In a highly original article, Town and Vistnes (2001) offered the first analysis that focused on the *ex ante* contribution of the supplier to the option demand intermediary. Their application was also to managed care. Unfortunately, their article misstates the key formula for computing WTP, thereby compromising their empirical validation of the WTP concept. Moreover, they provide no derivation of the formula, making it difficult for the reader to correct the error and to extend their work. In Appendix A, we rewrite their formula in our notation, contrast it with the formula we derive, and discuss the resulting errors.

4. A model of option demand

■ Our goal is to calculate each consumer's *ex ante* WTP to include a particular hospital in an MCO's network. This is his WTP as calculated at the beginning of the year, at the time he selects his MCO, and prior to his falling ill and requiring hospitalization. We compute the *ex ante* value that a hospital brings to the network by summing this WTP over all consumers. An individual consumer's *ex ante* WTP is distinct from his *interim* WTP, which is his WTP contingent on knowing his medical diagnosis, but before he explores specific treatment options. To compute his *ex ante* WTP, however, we first determine his interim WTP under each possible realization of health.

The following example illustrates our methodology. Suppose consumer i, a young adult apparently in good health, is evaluating an MCO that offers him access for the next year to a network G of hospitals that includes hospital j. Hospital j is located far from his home and he can conceive of only one circumstance in which he would choose j for his care: congestive heart failure requiring a heart transplant, since hospital j is commonly thought to be the best heart transplant hospital in the region. Therefore, looking ahead, consumer i understands that should he be diagnosed with congestive heart failure, his interim WTP to have access to hospital j would be high, say \$60,000.[6] By contrast, if consumer i should tear a knee ligament, then his interim WTP to have access to hospital j would be low, say \$10, because there are several closer, more convenient hospitals that provide fine treatment for torn ligaments. Finally if he remains healthy, then his interim WTP for access to j is \$0.

We now translate interim WTP into *ex ante* WTP. This is calculated as his interim WTP across all possible diagnoses (including healthy) weighted by each diagnosis's probability. Consumer i understands that his probability of remaining healthy for the next year is high, of injuring a knee ligament is low, and of developing congestive heart failure is negligible. Therefore his *ex ante* WTP to have j included in the network might be only \$5. If most of an MCO's enrollees are like consumer i, then the MCO will not pay hospital j a premium price for its services because it does not add premium value. If, however, there are several enrollees in the MCO's plan for whom congestive heart failure is likely, or if there are many enrollees who live close to hospital j, then the aggregate *ex ante* WTP across all enrollees may be quite high. Hospital j might use this as a bargaining lever to secure higher-than-usual rates from the MCO and capture part of the value it creates for consumers.

We formalize these concepts, first by defining the *ex post* expected utility of a patient who

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[6] This \$60,000 represents the difference between the dollar value of receiving the transplant at hospital j versus receiving it at the next-best transplant provider in the network, not the value of the transplant itself.

commits to obtain treatment for his realized illness at a specific hospital, and then by defining the expected interim utility of a consumer who knows his health state but has not begun the process of choosing among available hospitals. Finally, we aggregate the interim utilities to obtain the *ex ante* expected utility of a consumer who has neither learned his health state nor begun choosing among the available hospitals.

□ ***Ex post* expected utility.** Suppose the consumer requires medical treatment and can choose to be a patient at one hospital from the set G of network hospitals. The *ex post* expected utility of patient i who has decided to utilize hospital j is

$$\begin{aligned} U_{ij} &= \alpha R_j + H_j' \Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} \cdot X_i + \tau_3 T_{ij} \cdot R_j - \gamma(Y_i, Z_i) P_j(Z_i) + \varepsilon_{ij} \\ &= U(H_j, X_i, \lambda_i) - \gamma(X_i) P_j(Z_i) + \varepsilon_{ij}. \end{aligned} \tag{1}$$

$H_j = [R_j, S_j]$ is a column vector of hospital j's characteristics, where the vector of variables in R_j includes features that are common across all patient conditions such as teaching status, and the vector of variables in S_j includes condition-specific service offerings such as whether hospital j has delivery rooms. This structure implies that a particular hospital service benefits only patients whose diagnosis is related to that service. For instance, if patient i is admitted for a delivery, then the corresponding element in S_j is an indicator of the presence of a delivery room at hospital j. The column vector $X_i = [Y_i, Z_i]$ is patient i's type and includes both his socioeconomic characteristics Y_i and his clinical attributes Z_i that affect what services he may need. $P_j(Z_i)$ is the out-of-pocket price that patient i with clinical characteristics Z_i pays at hospital j. The variable λ_i is the geographical location of his home, and $T_{ij} = T_j(\lambda_i)$ is the approximate travel time from his residence zip code to hospital j. The function $\gamma(Y_i, Z_i)$ converts money to utils: it is the value in utils that patient i with characteristics (Y_i, Z_i) places on \$1. Finally, the error term represents the component of patient i's evaluation of hospital j that is personal and idiosyncratic.

The parameters in (1) are the unconditional marginal values of hospital attributes (vector α), patient-specific values of hospital characteristics (matrix Γ), travel costs (scalar τ_1 and vectors τ_2 and τ_3),[7] and the value of money as a function of the patient's type. Many elements of Γ in our estimation, namely those corresponding to irrelevant service-diagnosis pairs, are constrained to be zero. For example, since cardiac patients do not consider whether a hospital has a delivery room, we constrain the coefficient on the interaction between obstetric services and heart disease to be zero. Note also that specific hospital services, S_j, appear only via their interactions with patient characteristics, X_i.

In this setting, individual i will select hospital j if, for all hospitals $k \neq j$,

$$\begin{aligned} &\alpha(R_j - R_k) + (H_j - H_k)' \Gamma X_i + \tau_1(T_{ij} - T_{ik}) + \tau_2(T_{ij} - T_{ik})(T_{ij} - T_{ik}) X_i \\ &\quad + \tau_3(T_{ij} \cdot R_j - T_{ik} \cdot R_k) + \gamma(Y_i, Z_i)(P_j - P_k) \\ &= U(H_j, X_i, \lambda_i) - U(H_k, X_i, \lambda_i) \\ &> \varepsilon_{ik} - \varepsilon_{ij}, \end{aligned} \tag{2}$$

where we assume that (i) the ε_{ik} and ε_{ij} are distributed independently and identically with the standard double exponential distribution and (ii) the term $\gamma(Y_i, Z_i)(P_j - P_k)$ vanishes because the consumers in our estimation sample are selected to have health insurance of types that eliminate all meaningful out-of-pocket price differences among hospitals. We choose such a sample because out-of-pocket prices for hospital services are not available and are notoriously difficult to proxy.

Assumption (i) has two important implications. First, the probability s_{ij} that patient i chooses hospital j is given by the logit demand formula:

$$s_j(G, X_i, \lambda_i) = \frac{\exp[U(H_j, X_i, \lambda_i)]}{\sum_{g \in G} \exp[U(H_g, X_i, \lambda_i)]}. \tag{3}$$

[7] $T_{ij} \cdot X_i$ and $T_{ij} \cdot R_j$ denote interactions of T_{ij} and X_i with R_j, respectively.

An equivalent interpretation of s_j plays an important role below: if G is the set of hospitals in the market, then $s_j(G, X_i, \lambda_i)$ is hospital j's expected market share of type-X_i patients who live at location λ_i. Second, the unit variance of ε_{ij} scales all the coefficients in equation (1) that define *ex post* utility.

A major advantage of the utility specification in (1) is that the interaction of patient and hospital characteristics permits flexible substitution patterns across hospitals. This in turn allows for plausible own- and cross-price elasticities of demand and eliminates, or at least attenuates, the problems associated with using simple logit models to compute surplus.[8] As one hospital becomes less attractive, different patients will react in different ways. Depending on their illness, income, location, and other characteristics, some may remain, others may go to another nearby hospital, and others may choose to travel farther for care. This flexibility allows us to estimate more precisely the demand facing each hospital and thereby identify competitors.[9] Maximizing the likelihood function implied by equation (3) yields the underlying parameters of the utility function (1), with the exception of $\gamma(Y_i, Z_i)$.

□ **Willingness-to-pay to include hospital j in a network.** We seek patient i's *ex ante* WTP for the option to select hospital j from a network of hospitals G. To find this, we first compute, for each consumer type $X_i = [Y_i, Z_i]$, the decrease in i's interim utility when j is removed from the network. Thus, given the *ex post* expected utility specification in (1), the interim expected utility (up to an arbitrary constant) for access to network G of patient i with demographics Y_i, clinical attributes Z_i, and location λ_i is

$$V^{IU}(G, Y_i, Z_i, \lambda_i) = E \max_{g \in G}[U(H_g, Y_i, Z_i, \lambda_i) + \varepsilon_{ig}] = \ln\left[\sum_{g \in G} \exp(U(H_g, Y_i, Z_i, \lambda_i))\right]. \quad (4)$$

In deriving the formula for $V^{IU}(\cdot)$ we rely on the mathematical result that for choice set G, if u_g is the systematic component of utility and ε_g is an independently distributed standard extreme-value random variable, then the expectation of the maximum is $\ln[\sum_{g \in G} \exp(u_g)]$. Hospital j's contribution to this interim expected utility is

$$\begin{aligned} \Delta V_j^{IU}&(G, Y_i, Z_i, \lambda_i) \\ &= V^{IU}(G, Y_i, Z_i, \lambda_i) - V^{IU}(G/j, Y_i, Z_i, \lambda_i) \\ &= \ln\left\{\left[\sum_{k \in G/j} \frac{\exp(U(H_k, Y_i, Z_i, \lambda_i))}{\sum_{g \in G} \exp(U(H_g, Y_i, Z_i, \lambda_i))}\right]^{-1}\right\} = \left[\frac{1}{1 - s_j(H_j, Y_i, Z_i, \lambda_i)}\right], \end{aligned} \quad (5)$$

where G/j is the network G with hospital j excluded, and line three follows from the definition of $s_j(G, Y_i, Z_i, \lambda)$ in equation (3) and the identity $\sum_{g \in G} s_g = 1$.

Converting this to monetary terms gives, conditional on patient i being of type X_i, the interim WTP to retain hospital j as part of network G:

$$\Delta W_j^{IU}(G, Y_i, Z_i, \lambda_i) = \frac{\Delta V_j^{IU}(G, Y_i, Z_i, \lambda_i)}{\gamma(Y_i, Z_i)}. \quad (6)$$

[8] Trajtenberg (1989) uses logit models without individual-level data to compute surplus. Berry, Levinsohn, and Pakes (1995) and Petrin (2002) discuss the substitution pattern problem. Without individual data and a flexible functional form as in (1), the heterogeneity of individuals' choices is accounted for by a substantial variance on the error term, causing unrealistically high WTP values due to the resulting apparent patient loyalty.

[9] Another concern about logit demand models is the specification of the outside option. Because we do not observe patients who do not receive treatment, there is no clearly defined outside option in this case (also, nearly every San Diego resident receives treatment from a San Diego hospital). Thus the model implicitly assumes that there is a captive market of patients who must go to one of the hospitals.

Thus, suppose patient i with socioeconomic characteristics Y_i should learn that he has clinical characteristics Z_i. Given that he will choose the hospital in the network that maximizes his *ex post* expected utility, ΔW_j^{IU} is i's interim WTP to have hospital j included in the network G. Note that if consumer i of type X_i is healthy, then $\Delta W_j^{IU} = 0$ because a consumer who *knows* he is healthy does not value access to any hospital.

Let $f(Y_i, Z_i, \lambda)$ be the joint density of the demographics, clinical indications, and locations of all consumers who will be sufficiently ill during the next year to cause them to require hospitalization. Further, let $f(Z_i \mid Y_i, \lambda_i)$ be the conditional density of patient i's clinical characteristics Z_i if he has demographics and location (Y_i, λ_i). Given network G and patient i with demographics (Y_i, λ_i), i's *ex ante* WTP to include hospital j in G is

$$\begin{aligned}\Delta W_{ij}^{EA}(G, Y_i, \lambda_i) &= \int_Z \Delta W_j^{IU}(G, Y_i, Z_i, \lambda_i) f(Z_i \mid Y_i, \lambda_i) dZ_i \\ &= \int_Z \frac{\Delta V_j^{IU}(G, Y_i, Z_i, \lambda_i)}{\gamma(Y_i, Z_i,)} f(Z_i \mid Y_i, \lambda_i) dZ_i, \qquad (7)\end{aligned}$$

where Z is the set of all possible clinical indications. Summing this across all patients gives the population's *ex ante* WTP to include hospital j in network G (abbreviated henceforth as WTP for j):

$$\begin{aligned}\Delta W_j^{EA}(G) &= N \int_{y,\lambda} \Delta W_j^{IU}(G, Y_i, Z_i, \lambda_i) f(Y_i \mid \lambda_i) dY_i d\lambda_i \\ &= N \int_{Y,Z,\lambda} \frac{1}{\gamma(Y_i, Z_i)} \ln\left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i)}\right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i, \qquad (8)\end{aligned}$$

where Y and λ are the range of possible socioeconomic characteristics and geographic locations, $f(Y_i, \lambda_i)$ is the marginal density of consumers' demographics and locations, and the second line follows from equation (5).

The *ex ante* WTP for N ill consumers, expressed formally in equation (8), equals the *ex ante* WTP for the entire population—N ill and the rest healthy—that is enrolled in the managed care plan. The reason is that *ex ante* WTP for the entire population is a weighted sum of the change in interim WTPs for each consumer, whether ill or healthy. From an interim perspective, including hospital j in the network is good for those ill patients who might decide to choose hospital j, but of no consequence for healthy patients. Therefore, as noted above, the changes in interim utilities for healthy consumers are identically zero and drop out of the weighted sum, leaving (8) as the aggregate WTP for the population of all consumers in the managed care plan.

□ **Bargaining between the hospital and the MCO over consumers' WTP.** As they create provider networks, MCOs typically negotiate with hospitals over prices. MCOs have strong incentives to be tough in this bargaining because firms and other organizations that purchase managed care insurance for groups of individuals make their choices among competing plans in part on the basis of price.

Most of these purchasers also care about the value that the network provides their employees. In an afterword to a set of articles on employee benefits, Pauly (2001) finds substantial support for the claim that wages and benefits are fungible so that employers would be expected (i) to pass most, if not all, savings from managed care to employees and (ii) to charge employees for the extra cost of a more attractive hospital network. Thus, at least to some extent, employers have incentives to act as good agents for their employees. This gives a hospital with a favorable location and characteristics countervailing power against any MCO that is trying to negotiate a low price. Consequently, a reasonable hypothesis is that a hospital's profitability is directly related to consumers' WTP for its inclusion in the network. Hospitals that deliver greater incremental value to MCOs can presumably extract more profits from these negotiations in the form of higher prices and/or fewer quantity restrictions.

More formally, a necessary condition for the inclusion of hospital j in an MCO network G is that the WTP for it exceeds the additional costs its inclusion causes: $\Delta W_j^{EA}(G) > \Delta C_j(G)$. Including hospital j might cause the MCO's total costs to increase if including j causes some patients to switch from hospitals in G that have lower costs. Alternatively, if j is a relatively low-cost hospital, then $\Delta C_j(G)$ might be negative. Either way, the gain hospital j and the MCO can split is $\Delta W_j^{EA}(G) - \Delta C_j(G)$.

Depending on the parties' relative bargaining power (and neglecting issues of the incomplete information that they have about each other's payoffs), hospital j may capture either a large or small proportion of this gain. We assume that each hospital captures proportion α of it.[10] This assumption that all hospitals, no matter what their position in the marketplace, capture the fixed proportion α of the available gains is restrictive. It would be quite interesting to apply, for example, the more sophisticated model of multilateral bargaining of Stole and Zweibel (1996) to this situation. That model requires the intermediary to think strategically, e.g., excluding hospital j from the network might leave hospital k in a near-monopoly position, implying that it may be worth paying quite a high price to retain j.

We, however, stick with our myopic, reduced-form bargaining model because our focus here is on developing the WTP concept. Hospital j accepts a contract to provide care only if it at least covers its variable costs. Therefore, given that it captures proportion α of the gains from trade, the contribution it earns toward fixed costs and profit from the managed care segment of its business is

$$\pi_j = \alpha\left(\Delta W_j^{EA}(G) - \Delta C_j(G)\right) + u_j. \tag{9}$$

Though we call π_j "profit," we emphasize that it in fact refers to the incremental contribution above variable costs. Our goal is to measure the relationship between WTP and π_j in San Diego in 1991.

□ **Adaptation of the model to our dataset.** Shortcomings in our dataset require us to impose three additional assumptions on our model to make it estimable. This subsection discusses these assumptions and their implications. The first difficulty is that we do not have price variation in the data and therefore cannot directly identify the function $\gamma(Y_i, Z_i)$, which is the value of \$1 in terms of utils. This function plays a crucial role in equation (8) for consumers' WTP to include hospital j in the network:

$$\Delta W_j^{EA}(G) = N \int_{Y,Z,\lambda} \frac{1}{\gamma(Y_i, Z_i)} \ln\left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i)}\right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i.$$

We assume that the dollar value of a util is constant: $\gamma(Y_i, Z_i) = \gamma_P$. This allows us to rewrite (8) as

$$\begin{aligned}\overline{\Delta W}_j^{EA}(G) &= \gamma_P \Delta W_j^{EA}(G)\\ &= N \int_{Y,Z,\lambda} \ln\left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i)}\right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i.\end{aligned} \tag{10}$$

This index, in which $\overline{\Delta W}_j^{EA}(G)$ is WTP up to the unidentified scale factor γ_P, is calculable because both $s_j(G, Y_i, Z_i, \lambda_i)$ and $f(Y_i, Z_i, \lambda_i)$ are observable in the data. Fortunately, as we show below, it is also sufficient for our purpose of demonstrating WTP's practical potential as a measure of market power in option demand markets.

The assumption that $\gamma(\cdot)$ is constant is strong but arises naturally if each patient chooses among the hospitals in G as if he obeyed the following time sequence:

[10] The cooperative, complete-information Nash bargaining solution implies $\alpha = .5$. Brooks, Dor, and Wong (1997) provide a good discussion of bargaining models applied to hospital-insurer bargaining.

(i) At the beginning of the year, for each hospital j, patient i draws ε_{ij} latently from the standard extreme-value distribution. The interpretation is that if, for two hospitals j and k, $\varepsilon_{ij} - \varepsilon_{ik} > 0$, then the quantity $\rho_{ijk} = (\varepsilon_{ij} - \varepsilon_{ik})/\gamma_P$ expresses in monetary terms how much more patient i values using hospital j instead of hospital k, provided everything else is equal, i.e., ρ_{ijk} is the value of i's loyalty to hospital j relative to hospital k.

(ii) Sometime during the year, patient i learns his clinical condition Z_i.

(iii) Patient i recovers the latent vector $\varepsilon_i = (\varepsilon_{i1}, \ldots, e_{iJ})$ of loyalty premiums and chooses among the hospitals in G on the basis of equation (2).

This sequence implies that equation (10) is the correct formula for aggregating the interim utilities for each clinical indication Z_i into the overall WTP index $\overline{\Delta W_j^{EA}}(G)$ for a particular hospital j. Note that even with $\gamma(\cdot)$ specified to be constant, the flexible form of (1) permits, for example, elderly or high-income patients to reveal through their choices that minimizing travel time is more important for them than it is for younger or poorer patients.

The constant $\gamma(\cdot)$ assumption permits us to infer aggregate WTP from disease-specific information about market shares. To gain intuition as to why market share information informs us as to which clinical conditions Z_i have a large value $\Delta W_{ij}^{IU}(G, Y_i, Z_i, \lambda_i)$ and contribute most to $\Delta W_j^{EA}(G)$, consider an individual i who lives at location λ_i, has demographics Y_i, and can choose between two hospitals, j and k. Both hospitals are quite convenient for him, but j has a higher reputation for quality than k. Suppose interim, before i recovers his vector ε, the probability that he chooses j is .51 if he realizes diagnosis Z_A and .95 if he realizes diagnosis Z_B, a much more serious condition than Z_A. Therefore, for Z_A the random difference $\varepsilon_{ij} - \varepsilon_{ik}$ in his idiosyncratic preference terms dominates i's choice between hospitals j and k. The *ex post* expected utility difference $U(H_j, Y_i, Z_A, \lambda_i) - U(H_k, Y_i, Z_A, \lambda_i)$ is trivial in comparison.

By contrast, for diagnosis Z_B, the *ex post* expected utility difference $U(H_j, Y_i, Z_B, \lambda_i) - U(H_k, Y_i, Z_B, \lambda_i)$ dominates the expected idiosyncratic difference $\varepsilon_{ij} - \varepsilon_{ik}$ and leads to the .95 probability that i will choose hospital j. Inspection of equations (4) and (5) shows that this larger difference in *ex post* expected utilities for Z_B, in conjunction with the assumption of constant $\gamma(\cdot)$, implies that $\Delta V_j^{IU}(G, Y_i, Z_B, \lambda_i)$ (the incremental interim utility j offers if Z_B is realized) exceeds $\Delta V_j^{IU}(G, Y_i, Z_A, \lambda_i)$ (the incremental interim utility j offers if Z_A is realized). In particular, given constant $\gamma(\cdot)$, $\Delta V_j^{IU}(G, Y_i, Z_B, \lambda_i) > \Delta V_j^{IU}(G, Y_i, Z_A, \lambda_i)$ implies that $\Delta W_j^{IU}(G, Y_i, Z_B, \lambda_i) > \Delta W_j^{IU}(G, Y_i, Z_A, \lambda_i)$. Thus, if hospital j has high market shares in enough diagnoses, then consumers have a high WTP for its inclusion, provided those diagnoses are not too rare.

The second difficulty in our data is that we do not have sufficient information to calculate $\Delta C_j(G)$, the change in costs caused by adding hospital j to the network, with any degree of confidence. Creating such a measure is a difficult exercise, for it would require not only knowing where patients would reallocate themselves if j were not available in the network, but also information on the cost of treating each of those patients at the preferred alternative hospital. To simplify the analysis, we therefore assume that the incremental cost of treating a given condition is the same at all hospitals and, therefore, $\Delta C_j(G) = 0$ for all hospitals j.[11] We believe this assumption is more reasonable than it at first appears. Consider two points. First, the Medicare diagnosis related group (DRG) system is based on the idea that the expected cost of treating a particular diagnosis should not vary across hospitals. Second, differences in apparent average costs across hospitals for treating a particular DRG are, at least in part, accounted for by differences in average severity across hospitals and by differences in allocation of fixed costs. Suppose that severely ill patients within DRG Z_B consistently choose hospital j. This will cause j's accounting data to indicate high costs of treating Z_B, but this does not imply that $\Delta C_j(G) \neq 0$;

[11] With a sufficiently detailed estimate of each hospital's cost function—one that gives the cost of treating every condition at every hospital—it would be possible to use the choice model to determine where patients would reallocate when the network changes. Then the cost function could be used to estimate $\Delta C_j(G)$.

presumably other hospitals would have similarly high costs of treating these severely ill patients. Thus, $\Delta C_j(G) \neq 0$ only if hospital j is more or less costly than other hospitals, holding severity constant.

The third difficulty in our dataset is that we do not observe which hospitals managed care patients are eligible to select. To fill this vacuum, we assume that each MCO ℓ includes all hospitals in its network, i.e., G_ℓ is the network of the whole. Again, this is a strong assumption, though it does not appear to be far removed from reality and is supported by a straightforward theoretical argument. Based on discussions with managed care executives, our informed (but not well-documented) understanding is that networks in San Diego for the year we are studying were likely to be quite inclusive. Better documented is recent hospital membership in MCO networks within the state of Connecticut, which provides highly detailed data on hospital participation in managed care networks (Cogswell, 2002). According to year 2000 data, of the nine HMOs in the state, eight contract with at least 87% of the state's hospitals and 5 contract with at least 93%. Of the 15 PPOs, 13 contracted with 87% of the hospitals, and five contracted with 93%. Thus, in Connecticut recently, almost all networks consist of nearly all hospitals, which is consistent with using the network of the whole as a useful benchmark for computing WTP.

From a theoretical perspective, a simple argument shows that MCOs have a financial incentive to increase the size of their network. (Appendix B sketches this argument formally.) Increasing network size increases the *ex ante* expected utility of consumers by expanding their choice set. At the same time, it increases competition among the hospitals, reduces their market power, and thereby reduces the profits they are able to claim in their negotiations with MCOs. Therefore, we expect that if MCO ℓ does not include a particular hospital j in its network, then the reason is that j's inclusion would not significantly increase the value of the network that ℓ is offering its customers, i.e., WTP would only increase trivially if j were added. Note also that when we estimate versions of the model in which the price predictions are based on logit models estimated using only Medicare and fee-for-service patients—patients who do not face restricted choice sets—the results are largely unchanged.

These difficulties prevent us from estimating equation (9), $\pi_j = \alpha(\Delta W_j^{EA}(G) - \Delta C_j(G)) + u_j$, as we would if we had better data. The equation we actually estimate is

$$\pi_j = \frac{\alpha}{\gamma_P}\left(\overline{\Delta W}_j^{EA}(G)\right) + u_j = a\left(\overline{\Delta W}_j^{EA}(G)\right) + u_j. \tag{11}$$

Estimating (11) instead of (9) potentially introduces both omitted-variable and errors-in-variable bias into our estimate of $a = \alpha/\gamma_P > 0$. We analyze this bias here. To keep our discussion of how the different sources of bias interact as simple as possible, we assume that the measures $\Delta W_j^{EA}(G)$, $\overline{\Delta W}_j^{EA}(G)$, and $\Delta C_j(G)$ are all represented as deviations from their respective means. This eliminates all intercepts from the several regressions that are used in the analysis and considerably simplifies the notation.

Most obviously, our estimate of a is subject to omitted-variable bias because we assume $\Delta C(G) = 0$. Only if $\Delta W_j^{EA}(G)$ is uncorrelated with $\Delta C(G)$ is $\hat{a}$ free of omitted-variable bias. If, however, our assumption that $\Delta C_j(G) = 0$ is violated and, as plausibly might be argued, $\Delta C_j(G)$ and $\Delta W_j^{EA}(G)$ are positively correlated, then we can write $\Delta C_j(G)$ as

$$\Delta C_j(G) = \beta_1 \Delta W_j^{EA}(G) + \varepsilon_{1j}, \tag{12}$$

where β_1 is positive and close to zero, and ε_{1j} is a mean zero error term that is independent of $\Delta W_j^{EA}(G)$. In other words, β_1 is the regression coefficient that we would obtain if $\Delta C_j(G)$ were able to be regressed onto $\Delta W_j^{EA}(G)$.

The second source of bias is that we use $\overline{\Delta W}_j^{EA}(G)$ in the regression rather than $\Delta W_j^{EA}(G)$. The theoretically correct formula for WTP is equation (8):

$$\Delta W_j^{EA}(G) = N \int_{Y,Z,\lambda} \frac{1}{\gamma(Y_i, Z_i)} \ln\left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i)}\right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i.$$

We, however, out of necessity compute and use the related WTP measure, $\overline{\Delta W}_j^{EA}(G) = \gamma_P \widehat{\Delta W}(G)$, where $\gamma_P = E_{Y_i,Z_i}[\gamma(Y_i, Z_i)]$ and

$$\widehat{\Delta W}_j^{EA}(G) = \frac{N}{\gamma_P} \int_{Y,Z,\lambda} \ln\left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i)}\right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i;$$

this is just a restatement of our assumption that $\gamma(Y_i, Z_i) = \gamma_P$.[12] Certainly, however, our constant γ assumption is at least somewhat incorrect. To the extent that this induces mean zero errors in $\widehat{\Delta W}_j^{EA}(G)$ that are independent of $\Delta W_j^{EA}(G)$, the effect on $\hat{a}$ is the usual bias toward zero induced by errors in variables.

If, however, the errors are correlated with $\Delta W_j^{EA}(G)$, then additional bias is introduced. Such correlation is plausible if specialized, high-quality hospitals with high WTP attract patients with serious, very worrying diagnoses Z_i that lead them to assign a low utility value to money. That is, $\gamma(Y_i, Z_i) < \gamma_P$ for the patients of high-WTP hospitals and, conversely, $\gamma(Y_i, Z_i) > \gamma_P$ for patients of low-WTP hospitals. Thus, if $\widehat{\Delta W}_j^{EA}(G)$ is not an exact approximation of $\Delta W_j^{EA}(G)$ and is also represented as deviations about its mean, then we can write $\widehat{\Delta W}_j^{EA}(G)$ as the regression

$$\widehat{\Delta W}_j^{EA}(G) = \beta_2 \Delta W_j^{EA}(G) + \varepsilon_{2j}, \tag{13}$$

where β_2 is positive, perhaps somewhat less than one, and ε_{2j} is uncorrelated with $\Delta W_j^{EA}(G)$.

The overall effect of these several sources of bias is easily seen by substituting (12) and (13) into (9), the equation that we would estimate if we could, and then collecting terms so as to obtain (11), the equation that we do estimate:

$$\begin{aligned}
\pi_j &= \alpha\left(\Delta W_j^{EA}(G) - \Delta C_j(G)\right) + u_j \\
&= \alpha\left(\Delta W_j^{EA}(G) - \beta_i \Delta W_j^{EA}(G) - \varepsilon_{1j}\right) + u_j \\
&= \alpha(1-\beta_1)\left[\frac{\widehat{\Delta W}_j^{EA}(G) - \varepsilon_{2j}}{\beta_2}\right] - \alpha\varepsilon_{1j} + u_1 \\
&= \frac{\alpha(1-\beta_1)}{\beta_2\gamma_P}\overline{\Delta W}_j^{EA}(G) - \alpha\varepsilon_{1j} - \frac{\alpha(1-\beta_1)}{\beta_2}\varepsilon_{2j} + u_1 \\
&= a\overline{\Delta W}_j^{EA}(G) + \left[\alpha\varepsilon_{1j} - \frac{\alpha(1-\beta_1)}{\beta_2}\varepsilon_{2j} + u_1\right].
\end{aligned}$$

As stated above, β_1 might plausibly be expected to be positive and near zero, and β_2 might be expected to be somewhat less than one. Thus, to the extent that β_1 deviates from zero and β_2 deviates from one, the estimate $\hat{a}$ is subject to offsetting biases. In addition, $\hat{a}$ suffers from errors-in-variables bias toward zero because $\overline{\Delta W}_j^{EA}(G)$ is negatively correlated with the equation's error term:

$$\begin{aligned}
&E\left\{\overline{\Delta W}_j^{EA}(G)\left(\alpha\varepsilon_{1j} - \frac{\alpha(1-\beta_1)}{\beta_2}\varepsilon_{2j} + u_1\right)\right\} \\
&\quad = E\left\{\left(\beta_2\gamma_P\Delta W_j^{EA}(G) + \varepsilon_{2j}\right)\left(\alpha\varepsilon_{1j} - \frac{\alpha(1-\beta_1)}{\beta_2}\varepsilon_{2j} + u_1\right)\right\} \\
&\quad = -\frac{\alpha(1-\beta_1)}{\beta_2}\sigma_{22} < 0,
\end{aligned}$$

[12] Our constant assumption, if it is correct, trivially implies that $\gamma_P = E_{Y_i,Z_i}[\gamma(Y_i, Z_i)]$.

where we have assumed that the covariance between ε_{1j} and ε_{2j} is zero because there is no obvious reason why it should be positive or negative. Overall the bias is indeterminate: there are two downward sources of bias and one upward source. Our subjective sense is that none of these biases is large and that $\hat{a}$ is therefore a decent estimate of α/γ_P.

We end this discussion by noting that these difficulties can, at least in principle, be avoided if we had better data that allowed us to reliably estimate $\Delta C_j(G)$ for each hospital j. Given measures for $\Delta C_j(G)$, it is possible to identify both α and a simple form of the function $\gamma(Y_i, Z_i)$ as follows despite not having any variation in the out-of-pocket prices that patients face. Let the functional form for $\gamma(\cdot)$ be $\gamma(Y_i, Z_i) = \delta g(Y_i, Z_i; b)$, where δ is a scalar parameter and b is a short vector of parameters.

Define

$$\overline{\overline{\Delta W}}_j^{EA}(G) \equiv \delta \Delta W_j^{EA}(G)$$
$$= N \int_{Y,Z,\lambda} \frac{1}{\gamma(Y_i, Z_i; b)} \ln \left[\frac{1}{1 - s_j(G, X^C, X^S, \lambda_i)} \right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i.$$

The nonlinear equation to be estimated is then

$$\pi_j = \left(\frac{\alpha}{\delta}\right) \overline{\overline{\Delta W}}_j^{EA}(G; b) - \alpha \Delta C_j(C) + u_j = a_1 \overline{\overline{\Delta W}}_j^{EA}(G; b) - a_2 \Delta C_j(G) + u_j.$$

Doing so would be computationally intensive.

5. Empirical issues in validating the WTP measure

■ We validate our model by computing WTP and hospital profits for managed care patients and then estimating. If WTP is an appropriate measure of market power, then it should be strongly positively correlated with profits. Moreover, by regressing profits on WTP we estimate a, the parameter that translates WTP into profits.

Our procedure for validation entails three steps. First, we estimate the choice model to recover the parameters of the utility function. Second, we use these parameter estimates to compute estimates $\hat{s}_j(G, X_i, \lambda_i)$ of each hospital's market share for each discrete cell of patient characteristics (X_i, λ_i). These estimated shares are used in formula (10) to compute $\overline{\Delta W}_j^{EA}(G)$ for each hospital j.[13] Third, we run the regression in equation (11), using profits from managed care patients to estimate the coefficient a.[14] If WTP is a valid measure of hospital power, then a should be positive and significant. The obstacles to implementing this plan include the following:

(i) Including managed care patients in the choice model can lead to biased results because some of them face a restricted choice set. Managed care patients can be divided into two broad categories. Those in PPOs usually have unrestricted access to virtually all hospitals in their market. Those in HMOs usually face a narrower choice set, consisting of perhaps 80–90% of available hospitals. Moreover, some HMOs may provide incentives to physicians to steer patients to low-cost hospitals within the choice set. Ideally, the choice model should not include HMO patients.

(ii) Most publicly available hospital financial data report revenues for privately insured patients, which is sufficient to estimate variable profits obtained from those patients. However, it is not always possible to obtain revenue from managed care patients only.

[13] The reason that we use estimated shares rather than actual shares is that we subdivide our data into a large number of cells, some of which have only a very few elements. Using the empirical shares will be, for some cells, quite noisy estimates of the underlying expected shares. Using the estimated shares damps this noise and, if our choice model is good, approximates the true expected shares.

[14] We implicitly assume that managed care patients and other patients have similar utility functions.

(iii) There appear to be three hospitals in our data that have very few contracts with managed care payers. For these hospitals, MCO patients represent less than 4% of total admissions, whereas for the remaining hospitals they constitute more than 20% of admissions. Profit from managed care patients is near zero for any hospital that does not have a contract with a managed care provider. In this instance, our measure of WTP may provide an estimate of the profits these hospitals would realize following successful negotiations with MCOs, but such hospitals cannot be used in the profit-WTP regression.

These obstacles suggest that implementation of our model will vary according to the available data. Here we use 1991 data provided by California's Office of Statewide Health Planning and Development (OSHPD). OSHPD data, which has been widely used to study competition in health care, lumps together all HMO and PPO hospital patients. In response, we develop two alternatives.

First, in stage 1 of our analysis, we use only patients with insurers that offer unfettered choice of provider. These include indemnity insurance and Medicare patients under age 75. We implicitly assume that the preferences of indemnity and "younger" Medicare patients are identical to those of managed care patients, once we control for covariates such as disease characteristics and patient demographics. In a second specification, we estimate the choice model with indemnity patients, younger Medicare patients, and all MCO patients. HMO patients constitute about 30% of this sample.[15] Thus, the coefficients in the choice model may be biased. For example, if HMOs steer patients away from high-cost hospitals, then hospitals with high levels of staffing and equipment may appear to be less attractive, reducing their estimated WTP.

After estimating the parameters of patient utility functions using one of the two preceding samples, we compute the WTP for each hospital. The next step is to relate WTP to MCO profits. Unfortunately, OSHPD data do not separately report revenues for managed care patients. Thus we can only compute profits from MCO contracts with an unknown degree of precision. This gives us two options for comparing WTP and profits:

(a) Compare WTP based on only MCO patients with a noisy measure of profits from MCO contracts.
(b) Compare WTP based on all privately insured patients with a less noisy measure of profits from all privately insured patients.

The advantage of option (a) is that our model of WTP applies specifically to managed care. Option (b) therefore has the disadvantage that it is not fully based on a structural model of hospital profits. It also has, however, several offsetting advantages. First, it may recover a more precise relationship between WTP and profits by reducing the error in measuring profits. This is especially

TABLE 1 **Alternative Estimation Approaches**

	Logit Sample	WTP Sample	Benefit	Drawback
1.	M,I	H/P	All patients in choice model have unfettered access. Follows model in second stage.	Noisy measure of HMO profit; bias in stage 2.
2.	M,I	I, H/P	All patients in choice model have unfettered access. Better measure of profits.	Applies WTP formula to non-MCO patients.
3.	M,I,H/P	H/P	Possibly better prediction of MCO patient choice. Follows model in second stage.	Noisy measure of HMO profit, possible bias in choice model and in stage 2.
4.	M,I,H/P	I,H/P	Possibly better prediction of MCO patient choice. Better measure of profits.	Possible bias in choice model. Applies WTP formula to non-MCO patients.

Note: M = Medicare; I = indemnity (includes Blue Cross indemnity); H/P = HMO/PPO.

[15] HMO/PPO patients represent slightly less than half of all the patients that we consider. According to the 1994 Pulse survey, HMO patients represented about 62% of the total managed care enrollments in San Diego. Thus, we estimate that HMO patients represent about 30% of our multinomial logit sample. The Pulse survey was conducted by Inforum, a consulting firm.

likely if WTP turns out to be correlated with the prices that hospitals charge to indemnity patients. Second, it will better reflect the performance of hospitals that were attractive to MCO patients but failed to secure contracts. Finally, antitrust enforcers may be equally concerned about indemnity and MCO patients. To the extent that option (b) recovers an empirical regularity, this may prove helpful in predicting the effects of mergers on prices, even if it is not completely grounded in economic theory. Table 1 summarizes the various approaches to comparing WTP to profits.

6. Data

■ The primary data are a cross-section of San Diego area patients and hospitals, taken from the OSHPD 1991 Patient Discharge Report and Financial Disclosure Report. We select San Diego because it is large enough to have geographic submarkets, but not so large as to be computationally burdensome. Under the broadest definition, there are 25 acute care hospitals in the San Diego area. We omit three of these: two are extremely small, and the third is a Kaiser hospital.[16] Table 2 lists the remaining 22 San Diego hospitals and some of their characteristics. Of these 22 hospitals, five are municipal hospitals operated by local government agencies.[17]

There were 78,932 nonemergency admissions to the 22 hospitals that we consider. We retained the 41,083 patients for whom the insurer was listed as Medicare (under age 75), indemnity (listed as either fee-for-service or Blue Cross), or an HMO/PPO. Excluded patients include worker's compensation patients, who may have highly idiosyncratic preferences, and the

TABLE 2 **San Diego Hospitals (N = 22)**

	Patients in Sample	Control	Teach	Transplants	Delivery
Harbor View Health Partners	1,122	FP	N	N	N
HCA Hospital of San Diego, Inc.	2,718	FP	Y	Y	N
Mission Bay Memorial Hospital	615	FP	N	N	N
NME Hospitals, Inc.	2,055	FP	N	N	Y
Children's Hospital, San Diego	1,818	NFP	Y	N	N
Community Hospital of Chula Vista (CHCV)	999	NFP	N	N	N
Coronado Hospital, Inc.	316	NFP	N	Y	Y
Mercy Hospital	4,910	NFP	Y	N	Y
Paradise Valley Hospital (PVH)	681	NFP	N	Y	Y
San Miguel Hospital	145	NFP	Y	N	N
Scripps Memorial Hospital	526	NFP	N	N	N
Scripps Memorial, Chula Vista (SCV)	1,367	NFP	N	N	Y
Scripps Memorial, La Jolla	3,314	NFP	N	N	Y
Sharp Cabrillo Hospital	1,090	NFP	N	N	N
Sharp Memorial Hospital	6,587	NFP	Y	Y	Y
UCSD Medical Center	1,909	NFP	Y	Y	Y
Villa View Community Hospital	256	NFP	N	N	N
Fallbrook Hospital District	388	Munic.	N	N	Y
Grossmont District Hospital	3,295	Munic.	N	N	Y
Palomar Pomerado, Escondido	2,401	Munic.	N	N	Y
Palomar Pomerado, Poway	1,797	Munic.	N	N	Y
Tri-City Hospital District	2,774	Munic.	N	Y	Y

[16] Kaiser is an HMO that owns its own hospitals. Pragmatically, Kaiser was eliminated because it only reports a subset of the data reported by other hospitals. Additionally, non-Kaiser patients do not generally go to Kaiser hospitals, and vice versa.

[17] Additional hospital data and a map of San Diego hospitals are available at http://www.kellogg.nwu.edu/faculty/dranove/research/.

TABLE 3 Patient Variables (N = 41,083)

Variable	Type	Mean	Standard Deviation	Minimum	Maximum
Male	Y	.336	.472	0	1
Elderly	Y	.314	.464	0	1
White	Y	.794	.404	0	1
Income, $1,000's	Y	16,640	5,999	0	40,268
Expected Length of Stay	Y	5.539	7.533	0	415
%Travel (*pcttravel*)	Y	.219	.060	.128	.581
Number of Other Procedures	Y	1.448	1.391	0	4
Number of Other Diagnoses	Y	2.092	1.442	0	4
Driving Time (minutes to chosen hospital)	—	15.801	9.995	1	79
Travel Distance (miles to chosen hospital)	—	8.884	7.525	.3	61.1
Driving Time (minutes to all hospitals)	—	29.346	16.751	1	92
Travel Distance (miles to all hospitals)	—	19.848	13.775	.2	69.3
Medicare Dummy	—	.268	.443	0	1
Blue Cross/Blue Shield Dummy	—	.046	.210	0	1
Indemnity Dummy	—	.206	.405	0	1
HMO/PPO Dummy	—	.479	.500	0	1
Neurological Diagnosis	Z	.031	.174	0	1
Respiratory Diagnosis	Z	.036	.186	0	1
Cardiac Diagnosis	Z	.115	.319	0	1
Labor/Delivery	Z	.285	.452	0	1
MRI/CT Admission	Z	.042	.200	0	1
Psychiatric Admission	Z	.025	.157	0	1

uninsured, who may face a limited choice set. We also exclude Medicaid patients because some hospitals may shun such patients due to low reimbursements.

The hospital characteristics used in the analysis are a general hospital characteristic (R_j) and measures of specific service offerings (S_j). Variables in R_j include *Profit* and *Teach*, dummy variables indicating a hospital's type of control and whether it is a teaching hospital, respectively; *nursing intensity* equals nursing hours converted to annual full-time-equivalent nurses, divided by patient days in 1990. *Equipment intensity* is the dollar value of equipment, divided by patient days in 1990.[18] The service offerings dummies, S_j, that we include indicate whether the hospital specializes in each of the following service lines: diseases of the nervous system, diseases of the respiratory system, cardiac care, labor and delivery, magnetic resonance imaging, and psychiatric care.

Descriptive statistics for San Diego patients are in Table 3. *Male*, *white*, and *elderly* indicate the patient's gender, race, and whether the patient is over age 60. *Income* is taken from the 1990 census and is matched to patients by zip code and by race for the categories white, black, and other. We employ three indicators of severity. The first two are the *number of other procedures* and the *number of other diagnoses*, both of which are truncated at four. The third measure of severity, *pcttravel*, is to our knowledge, new to health services research. We compute a value of *pcttravel* for each DRG by starting with the universe of patients living in rural California counties that have hospitals. We then compute, for every DRG, the percentage of rural patients who leave their county of residence to receive treatment. We suppose that if *pcttravel* is high, then the DRG must require complex treatment, which explains why patients are more likely to bypass their local hospital.

In addition to these hospital and patient characteristics, our choice model includes the approximate driving time (*timeij*), computed using the travel time from patient i's home zip code centroid

[18] We use 1990 patient days to avoid endogeneity bias.

to hospital j's street address. We used the "driving directions calculator" on the Mapquest.com web page to generate the time and distance data. The Mapquest algorithm accounts for actual driving conditions, and considers turns, stoplights, and freeway travel.

7. Estimation

■ The first step toward obtaining the measure of interest, aggregate willingness to pay, is estimating the utility function in equation (1) using standard multinomial logit techniques. The choice set in the estimation consists of the 22 San Diego hospitals listed in Table 2. The predictors include five types of variables. First are hospital-specific variables that are constant across all patient conditions (R_j), including ownership type, teaching status, a dummy for transplant services (indicating a "high-tech" hospital), and measures of equipment and nursing intensity. Second, we include travel time, T_{ij}, as well as interactions of travel time with the hospital-specific variables ($T_{ij} \cdot R_j$). The third set of variables, ($T_{ij} \cdot X_i$), includes interactions between travel time and the patient-specific clinical and demographic variables listed in Table 3. These interactions allow willingness to travel to vary with patient type and condition.

Fourth and fifth are the interactions between hospital characteristics and patient characteristics, $[R_j, S_j]'\Gamma[Y_i, Z_i]$. These include interactions between patient characteristics and hospital characteristics ($R_j'\Gamma_1 X_i$), and interactions between diagnosis dummies and hospital service offerings ($S_j'\Gamma_2 Z_i$).[19] An example of the former is an interaction between severity and teaching status. An example of the latter is a "match" interaction between the dummy for an obstetric admission and whether the hospital has a dedicated labor and delivery room. Similar "match" interactions are included for cardiac admissions, respiratory admissions, psychiatric admissions, and neurological admissions.

We estimate the multinomial choice model twice, first using only indemnity and younger Medicare patients, and then with MCO patients added. The pseudo R^2 for the two estimations are .367 and .355 respectively.[20] For the current work, one important finding is that the coefficient on travel time is negative and highly significant. There are also many significant interactions between patient and hospital characteristics, suggestive of substitution patterns that vary greatly across patient types.

We use the estimated coefficients to compute the WTP for inclusion of each of the 22 hospitals in the network, as indicated in equation (10). As discussed above, we do this twice: first for MCO patients only, and then for MCO and indemnity patients. Thus, we have four different estimates of WTP (two estimates of the utility function, and two computations of WTP per estimate).

Our next empirical task is to compute profits. For those models where we compute WTP for indemnity and MCO patients, we subtract contractual deductions (excluding deductions attributable to Medicare and Medicaid) from gross private-payer revenue to obtain net revenue attributable to private payers. For models where we compute WTP for MCO patients only, we use the percentage of all private discharges at each hospital that are categorized as HMO/PPO to scale down revenue from all private payers. In either case, we restrict attention to profits from daily hospital services (DHS). This category includes nursing and intensive care services, for example, but excludes ancillary services. We exclude the latter because OSHPD includes revenues from outpatient care in the total revenues from ancillary services. There are many substitutes for outpatient services, including physician and clinic services, so including outpatient revenue may muddy the analysis of market power.

To estimate costs, we compute the DHS average direct cost per admission for all patients (OSHPD does not break costs down by payer type). We then multiply by the number of discharges for MCO patients or privately insured patients, as appropriate. Profits equal net revenues minus

[19] If the kth element of H_j is in S_j and the ℓth element of X_i is in Y_i, then $\Gamma_{\ell,k}$ is constrained to be zero. For example, *income* is not interacted with a dummy indicating whether the hospital has psychiatric services (an element of S_j), but *income* is interacted with the dummy for teaching status (an element of R_j).

[20] Coefficient tables are available at http://www.kellogg.nwu.edu/faculty/dranove/research/.

direct costs. Note that this computation excludes indirect costs, and therefore reflects the profits available when an MCO negotiates with a hospital.

8. Results

■ Figure 1 plots profits from daily hospital services against WTP for the four combinations of first- and second-stage samples. Table 4 reports the profit and WTP values for each hospital, and Table 5 reports the results of the corresponding regressions. In all four cases, there is a strong, precisely estimated positive relationship between WTP and profits, with correlations ranging from .75 to .90.[21] The results are insensitive to which model is used, reflecting the fact that the various measures are all highly correlated: the correlations across the four WTP measures range from .78 to .99, while the two profit measures have a correlation of .94. Depending on the model, when evaluated at the mean, a 10% increase in WTP corresponds to an increase in profits between 9.6% and 10.6%.

To illustrate how WTP translates into profits, consider model 1, in which each one-unit increase in WTP increases profits from MCOs by $2,233 (with a standard deviation of $412). To interpret the magnitude of this estimate, consider a successful nonprofit hospital, Sharp Memorial Hospital (WTP = 2,132), and a lesser hospital, Community Hospital of Chula Vista (WTP = 310). Using the results of model 1, the WTP difference of 1,826 generates a managed care profit difference of $4.1 million.

Three points should be emphasized about this analysis. First, although we estimate the multinomial choice problem using the five municipally operated hospitals, we exclude them from this profit-WTP analysis because they admit a disproportionate number of uninsured patients and can use local taxing power to offset revenue shortfalls. Thus, they may use their market power in a different manner than we hypothesize for the 17 privately owned hospitals that are used in the plots.

Second, in models 1 and 3, which use managed care profits as the dependent variable, the three hospitals lowest on the profit axis are those that apparently did not have managed care contracts in 1991. Third, in all four models, the most obvious outlier is the University of California, San Diego (UCSD) hospital. UCSD, while generating a high WTP, reports an extremely high level of profits. Indeed, if we exclude UCSD, the correlation between WTP and profits increases to about .95. Although there are several teaching hospitals in the market, UCSD is the only member of the Council of Teaching Hospitals and the only university hospital in the market. It is possible that this confers a higher WTP than we are able to capture with the variables at hand. Another possibility is that the method used to allocate costs and revenue across the hospital and the parent university may misstate the true profits at UCSD.

An interesting application of our methodology is to assess whether nonprofits or for-profits are more likely to exploit their market power. In one recent hospital merger case, the courts accepted arguments that nonprofits are unlikely to use market power to raise prices.[22] Inspection of the WTP-profit plots would shed light on this claim. If the slope is steeper for the for-profits, this would be consistent with the theory that they are more likely to exploit their market power. We find no support for this claim—in fact, the nonprofit line appears slightly above the for-profit line. When we separately estimated for-profit and nonprofit slopes, we were unable to reject the null hypothesis that the slopes are identical; the slope of the for-profit line is always smaller than the slope of the nonprofit line.

To further understand the sources of hospital pricing power, examine again equation (10),

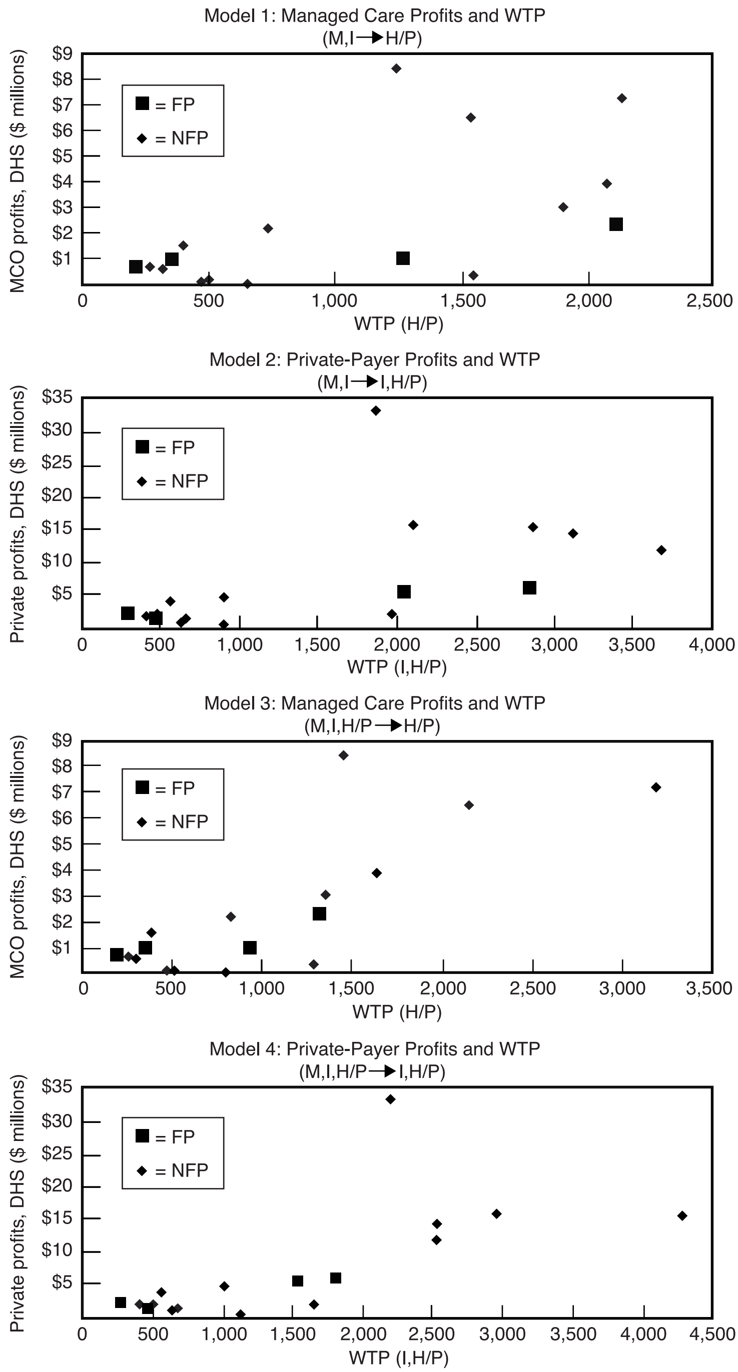
$$\overline{\Delta W}_j^{EA}(G) \equiv N \int_{Y,Z,\lambda} \ln\left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i)}\right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i,$$

[21] All regressions are without a constant, as implied by the model in Section 2. As the plots suggest and our bargaining model implies, if a constant is included, it is not significantly different from zero.

[22] *FTC* v. *Butterworth Health Corp*., W.D. Michigan 1997.

FIGURE 1

PROFITS AND WTP



the formula for WTP. Think of each triple (Y_i, Z_i, λ_i) as specifying a distinct market segment of patients who all have demographic characteristics Y_i, clinical indications Z_i, and location λ_i. The formula states that total WTP is the sum of segment WTPs and that, for a segment, WTP for hospital j is greater when it offers services and facilities that patients—whether local or distant—reveal as highly valued through awarding it a high market share. To obtain a high share,

TABLE 4 Willingness to Pay and Profits

		Willingness to Pay				Profits ($1,000s)	
	Logit Sample:	M,I	M,I	M, I,H/P	M, I,H/P	Private-	Manage
Hospital	WTP Sample:	I,H/P	H/P	I,H/P	H/P	Payer	Care
Scripps Memorial, Chula Vista (SCV)		906.4	734.1	1012.2	818.7	$4,853	$2,198
Children's Hospital, San Diego		3679.4	1900.3	2525.6	1343.6	$11,900	$3,015
Coronado Hospital, Inc.		658.4	501.2	680.7	516.8	$1,413	$143
Sharp Cabrillo Hospital		561.3	394.5	555.9	386.8	$4,008	$1,534
Sharp Memorial Hospital		2865.0	2131.6	4278.1	3191.4	$15,600	$7,202
San Miguel Hospital		902.9	642.8	1124.1	799.9	$531	$20
Mercy Hospital		2101.6	1536.3	2959.5	2148.5	$15,800	$6,471
Paradise Valley Hospital (PVH)		1965.3	1544.6	1641.3	1273.0	$2,199	$337
Scripps Memorial, La Jolla		3119.3	2077.0	2528.6	1633.1	$14,400	$3,933
UCSD Medical Center		1871.1	1234.4	2200.3	1448.5	$33,200	$8,418
Villa View Community Hospital		640.2	467.6	642.7	468.2	$1,017	$89
Community Hospital of Chula Vista (CHCV)		413.4	309.5	400.7	298.6	$1,985	$605
Scripps Memorial Hospital		480.0	260.7	492.3	265.5	$2,075	$641
NME Hospitals, Inc.		2840.0	2104.4	1802.1	1318.9	$6,145	$2,353
Harbor View Health Partners		456.2	343.5	457.4	349.5	$1,702	$1,005
Mission Bay Memorial Hospital		283.2	197.2	259.1	180.7	$2,515	$734
HCA Hospital of San Diego, Inc.		2046.3	1262.1	1520.3	932.3	$5,699	$1,019
Fallbrook Hospital District		1769.3	384.3	1704.9	376.3	$608	$1
Grossmont District Hospital		1721.4	1278.3	1577.9	1161.2	$6,058	$2,185
Palomar Pomerado, Escondido		2646.8	1049.5	2688.6	1063.4	$12,400	$943
Tri-City Hospital District		3138.8	1753.7	3131.2	1745.7	$10,600	$4,158
Palomar Pomerado, Poway		2812.4	1649.4	2743.7	1590.7	$1,399	$570

Note: M = Medicare; I = indemnity (includes Blue Cross indemnity); H/P = HMO/PPO.

hospital j must have above-average amounts of characteristics (R_j, S_j) that interact positively with the characteristics (Y_i, Z_i, λ_i) of that segment's patients. Finally, for overall WTP to be high, the hospital's high shares must not be restricted to "inconsequential" segments, that is, segments with small values of $f(Y_i, Z_i, \lambda_i)$.

We use these ideas to illustrate how excellence in specific diseases can contribute significantly to *ex ante* bargaining power. Consider the following exercise: partition hospital j's contribution to aggregate *ex ante* utility, $\overline{\Delta W}_j^{EA}(G)$, into components attributable to each of the 475 DRGs in the data. The component for DRG $\tilde{Z}_i$ is defined to be

$$\overline{\Delta W}_j^{EA}(G, \tilde{Z}_i) = N \int_{Y,\lambda} \ln\left[\frac{1}{1 - s_j(G, Y_i, \tilde{Z}_i, \lambda_i)}\right] f(Y_i, \tilde{Z}_i, \lambda_i) dY_i d\lambda_i, \qquad (14)$$

so that $\sum_{\tilde{Z}_i \in Z} \overline{\Delta W}_j^{EA}(G, \tilde{Z}_i) = \overline{\Delta W}_j^{EA}(G)$.[23]

Now consider two dramatically different hospitals, the University of California, San Diego Medical Center (UCSD) and Scripps Memorial Hospital of Chula Vista (SCV). UCSD is a high-tech teaching hospital, while SCV is a "plain vanilla" community hospital. Both have delivery services. *A priori,* neither hospital is predicted to have a higher aggregate contribution to WTP. UCSD may be a higher-quality hospital, but SCV could have a better location, be in a higher-income area, or have fewer nearby rivals. We expect, however, the higher-quality UCSD to generate relatively more of its total WTP from more severe DRGs. To demonstrate this, we compute the

[23] Note that the weighting by $f(Y, Z, \lambda)$ causes hospitals' values to tend to move together as the probability of contracting an ailment is independent of the hospital chosen upon contraction.

TABLE 5 Profit and Willingness to Pay

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Private Payer Profit	17	$7,362,361	$8,516,887	$531,282	$33,200,000
MCO Profit, all private hospitals	17	$2,336,292	$2,652,812	$20,275	$8,417,834
MCO Profit, >4% HMO patients only hospitals with	14	$2,818,887	$2,690,646	$337,343	$8,417,834
WTP, Model 1	17	1,517.07	1,114.37	283.23	3,679.41
WTP, Model 2-a	17	1,037.75	722.42	197.22	2,131.57
WTP, Model 2-b	14	1,145.01	755.50	197.22	2,131.57
WTP, Model 3	17	1,475.36	1,120.20	259.06	4,278.15
WTP, Model 4-a	17	1,022.00	794.69	180.67	3,191.36
WTP, Model 4-b	14	1,113.50	849.26	180.67	3,191.36

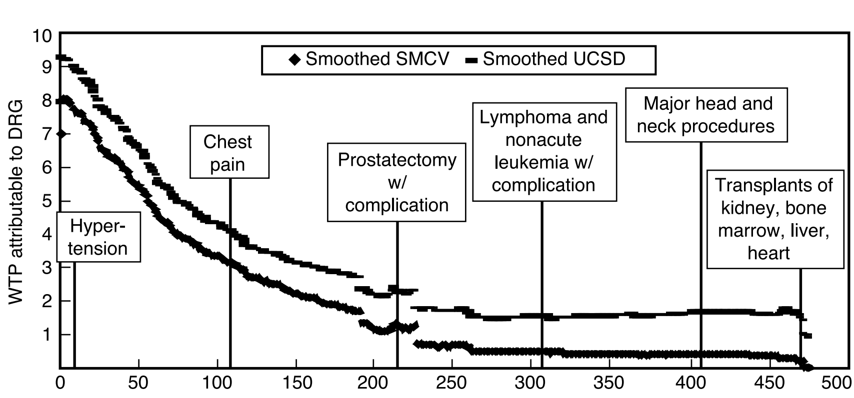
Model	1-a	1-b[a]	2	3-a	3-b[a]	4
N	17	14	17	17	14	17
Logit sample	M,I	M,I	M,I	M, I,H/P	M,I	M, I,H/P
WTP sample	H/P	H/P	I,H/P	H/P	H/P	I,H/P
Dependent variable	MCO Profits	MCO Profits	Private-Payer Profits	MCO Profits	MCO Profits	Private-Payer Profits
Independent variable	WTP(H/P)	WTP(H/P)	WTP(I,H/P)	WTP(H/P)	WTP(H/P)	WTP(I,H/P)
Coefficient	2233.11	2304.71	4654.33	2419.05	2516.01	5069.10
(Standard error)	(412.16)	(451.98)	(922.97)	(308.24)	(322.39)	(820.82)
Adjusted R^2	.6252	.641	.590	.7809	.8106	.686

Note: M = Medicare, I = indemnity (includes Blue Cross indemnity), H/P = HMO/PPO.
[a]Excludes three hospitals with <4% admissions from HMO-insured patients.

DRG-specific WTP components $\overline{\Delta W}_j^{EA}(G, Z_i)$ for UCSD and SCV. Figure 2 shows these values for each hospital where DRGs are sorted by increasing severity (as measured by *pcttrv*).[24] While UCSD is uniformly above SCV, meaning that for every DRG it generates more WTP by being in the choice set, the contribution gap in percentage terms widens above the median-severity DRG,

FIGURE 2

ITEMIZATION OF WTP BY DRG FOR UCSD AND SCRIPPS MEMORIAL CHULA VISTA (SCV)



[24] The data are smoothed using Cleveland's lowess running-line smoother and a bandwidth of .8.

and the value of SCV falls to zero at the highest level of severity.[25] This shows how a hospital, even if its overall market share is low, can gain leverage by successfully specializing in specific segments that are important to consumers.

9. Using WTP for antitrust market definition

■ Implementing the SSNIP criterion requires predicting how prices will change if two or more sellers set price as if they were a merged entity, holding costs constant. We now demonstrate how to use the WTP measure for this purpose. We do this in two steps. First, we estimate the increase in profit that hospitals can obtain postmerger. Then, using reasonable assumptions about price/cost margins, we estimate the associated change in prices.[26]

In general, merged entities enjoy greater market power because they can coordinate pricing. The same principle applies here: two merged hospitals increase their market power by coordinating their decision to join an MCO. To see how this affects WTP, consider hospitals j and k that have similar services and reputations and are geographically close together, but do not have any nearby competitors. Suppose they are independent and hospital k, but not j, is excluded from MCO A's network. Patients enrolled in A may only have a small WTP for adding hospital k to the network because the included hospital j is an excellent substitute. Similarly, if j were excluded and k included, then enrollees' WTP for j would also be small. Thus the sum, $\overline{\Delta W}_j^{EA}(G) + \overline{\Delta W}_k^{EA}(G)$, would be small.

Now suppose j and k merge and inform MCO A that it must include both j and k in its network if it wants either one. If A excludes both j and k, then its enrollees' WTP for the bundle j and k is likely to be large because there is no nearby substitute. In this case, j's and k's joint WTP may greatly exceed the sum of their isolated WTPs: $\overline{\Delta W}_{j+k}^{EA}(G) \gg \overline{\Delta W}_j^{EA}(G) + \overline{\Delta W}_k^{EA}(G)$. The formula for computing joint WTP (denoted by $\overline{\Delta W}_{j+k}^{EA}(G)$) is the straightforward generalization of (10):

$$\overline{\Delta W}_{j+k}^{EA}(G) = N \int_{Y,Z,\lambda} \ln\left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i) - s_k(G, Y_i, Z_i, \lambda_i)}\right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i. \tag{15}$$

Quick inspection of this equation may suggest that $\overline{\Delta W}_{j+k}^{EA}(G)$ necessarily exceeds $\overline{\Delta W}_j^{EA}(G) + \overline{\Delta W}_k^{EA}(G)$. This is incorrect, however, because if two hospitals are far enough apart, then hospital j will have zero market share in each market segment (Y_i, Z_i, λ_i) in which k has positive share, and, exactly parallel, k will have zero share in each segment in which j has positive share. Simply put, merging a San Diego hospital with a Boston hospital is unlikely to increase their market power.

The formula we use to estimate the profit effect of a merger between hospitals j and k is

$$\Delta\hat{\pi}_{j+k} = \hat{a}\left[\overline{\Delta W}_{j+k}^{EA}(G) - \overline{\Delta W}_j^{EA}(G) - \overline{\Delta W}_k^{EA}(G)\right], \tag{16}$$

where $\hat{a}$ is the coefficient on WTP from the regression in Table 5. This takes the empirically observed relationship between WTP and profits and uses it to project how much a merger-driven increment to WTP would permit the combined hospitals to increase their profits. While we have empirically demonstrated the relationship between WTP and profits in the cross-section, we have yet to empirically study the relationship between the change in profits and the change in WTP after mergers. Though illustrative of the methodology, the remaining examples have not been validated on actual mergers.

[25] UCSD has a better location, north of downtown, than does SCV in the lower-income south suburban area. UCSD does face more geographically close rivals, including two other high-tech hospitals, Mercy and Sharp Memorial.

[26] The simple bargaining model suggests that it is more appropriate to regress profits on WTP rather than directly regress prices on WTP.

TABLE 6 Effects of Chula Vista Mergers

	Model			
Merger	1[a]	2[b]	3[a]	4[b]
Increase in WTP				
SCV and PVH	274.64	33.6	222.84	27.66
SCV and CHCV	59.88	78.05	62.74	82.15
PVH and CHCV	55.7	73.2	47	62.35
All three	422.96	524.38	361.59	453.31
Profit Increase Per Private Discharge				
SCV and PVH	$144.48	$172.68	$126.99	$153.97
SCV and CHCV	$28.94	$41.56	$32.84	$47.64
PVH and CHCV	$77.17	$77.15	$7.53	$71.57
All three	$18.28	$221.19	$166.96	$208.26
Percentage Increase in Profit				
SCV and PVH	8.94%	14.07%	9.36%	14.74%
SCV and CHCV	4.26%	7.23%	4.94%	8.40%
PVH and CHCV	2.23%	3.76%	2.63%	4.41%
All three	12.12%	19.50%	13.30%	21.45%
Percentage Increase in Price				
SCV and PVH	10.97%	12.46%	9.64%	11.11%
SCV and CHCV	1.95%	2.74%	2.22%	3.15%
PVH and CHCV	3.52%	3.65%	3.22%	3.38%
All three	11.39%	13.98%	10.55%	13.16%

[a]Profit computed as $Q^{MCO} AR(Q^{Private}) - AC(Q)Q^{MCO}$.
[b]Profit computed as $Q^{Private} AR(Q^{Private}) - AC(Q)Q^{Private}$.

We first consider Chula Vista, a suburb of San Diego that lies about 11 miles south of downtown. There are two hospitals within Chula Vista proper, Scripps Memorial and Community Hospital of Chula Vista (CHCV), and one hospital roughly midway between Chula Vista and downtown San Diego, Paradise Valley Hospital (PVH). We consider this suburb because it bears directly upon a key issue in many hospital merger cases. Due to its high patient outflows (over 30%), courts using Elzinga and Hogarty–type methods would most likely rule that Chula Vista was not a well-defined geographic market and instead deem that the relevant market includes at least San Diego and its suburbs. As a result, such a court would be likely to conclude that the effects of a merger in Chula Vista would be trivial. However, our calculations indicate that Chula Vista is a well-defined market and that the traditional approach may be incorrect.

Table 6 reports the results of simulating the effects of mergers among the three Chula Vista hospitals. In keeping with SSNIP guidelines, we assume that costs are unchanged. Our results indicate that mergers in this suburb could lead to significant increases in profits. Should all three hospitals merge, the estimated effect on profits ranges from 12.1% to 21.5%, depending on the model. Depending on the hospitals involved, pairwise mergers would lead to increases in profits of 2.2% to 14.7%.[27]

The SSNIP question is generally formulated in terms of prices rather than profits. The bottom panel of Table 6 shows the increase in the average revenue (price) of an inpatient day, for each of

[27] These compare postmerger profits with the sum of merging hospitals' premerger profits. Note that PVH appears to have few contracts with managed care providers, whose patients account for only 7.2% of admissions at PVH. Thus, the somewhat larger percentage increases for mergers involving PVH in columns (2) and (4) in part reflect the lower baseline.

TABLE 7 Other Mergers (Based on Model-4 Results)

Merger	WTP Gain	% Increase Profit	Patient-Weighted Premerger AR	% Increase in Price	Per Discharge Increase in Private-Pay Profit	Miles (Minutes)	Number Teaching	Number Transplant	Number Delivery
Sharp Memorial [a] and UCSD	463.3	7.15%	27,18.4	3.42%	$93.11	5.2 (10)	2	2	2
Scripp's La Jolla and HCA[b]	233.8	5.78%	2,322.5	5.98%	$106.44	1.5 (3)	1	1	1
San Miguel and Mercy[c]	115.7	2.83%	2,175.9	2.53%	$55.00	1.2 (3)	2	0	1
Paradise and HCA[d]	36.1	1.14%	2,339.7	1.15%	$26.90	19.6 (26)	1	2	1
Villa View and Coronado[e]	17.8	1.35%	2,189.6	1.90%	$41.55	9.9 (22)	0	1	1
Scripps Chula Vista and Mission Bay[f]	4.3	.34%	1,509.1	.17%	$2.54	16.4 (23)	0	0	1

[a]Sharp Memorial and UCSD are near downtown San Diego.
[b]Scripps La Jolla and HCA are a northern satellite-pair.
[c]San Miguel and Mercy are both near downtown San Diego.
[d]Paradise and HCA are on opposite sides of downtown San Diego.
[e]Villa View is in northeast San Diego and Coronado is near downtown.
[f]Scripps and Mission Bay are on opposite sides of downtown San Diego.

the four models under the assumption that quantity is unchanged.[28] These price changes reflect the increases in average revenue necessary to generate the predicted increase in profits, given the premerger number of patients, average revenue, and average cost at each hospital. The predicted increase for a three-way merger is between 10.5% and 14.0%, while pairwise mergers generate price increases ranging from 2.0% to 12.5%. Of the two-way mergers, only the SCV and PVH merger has a substantial predicted effect. In large part, this probably reflects the absence of labor and delivery services—a particularly important service line—at CHCV. On balance, these increases suggest that a merger among all the Chula Vista hospitals would lead to a SSNIP and that this suburb in fact constitutes a relevant antitrust market.

After defining the market, the next step is to determine if a merger in that market is likely to harm consumers. This often entails a comparison of predicted price increases and cost savings. For example, our model predicts a price increase of about 10% should SMCV and PVH merge. Research on the likelihood of realizing comparable costs savings is mixed. Connor, Feldman, and Dowd (1998) find that hospital mergers are unlikely to produce savings of more than 3–4%, while Dranove and Lindrooth (2003) find that systems acquisitions do not generate savings, though mergers in which hospitals consolidate licenses generate savings of about 14%.

Table 7 shows the results of simulating the effects of six other potential mergers, using the estimate of $\hat{\alpha}$ from model 4. The first merger, between Sharp Memorial and UCSD, involves two hospitals near downtown San Diego, roughly five miles apart. The modest price increase of 3.4% reflects a combination of service overlap—both are teaching hospitals offering labor and delivery—and geographic proximity, offset by the presence of eight other downtown hospitals. Compare this to the San Miguel/Mercy merger. These downtown hospitals are only 1.2 miles apart, but they lack specialized service overlap. The predicted price increase is even smaller than for UCSD/Sharp Memorial. Based on these findings, it appears that it would take much or all of the downtown area to constitute a SSNIP market.

We also simulate a merger among a pair of hospitals in La Jolla, a large suburb 11 miles north of downtown San Diego. Despite modest service overlap, a merger of Scripps Memorial of La Jolla and HCA Hospital of San Diego (HCA) has a predicted price increase of 6.0%, suggesting that

[28] Under a purely capitated system, quantity is independent of the lump-sum transfer. If the marginal price consumers pay out of pocket increases as a result of the merger, then quantity would fall and the calculations in Table 6 would underpredict the price increase.

this suburb may also be a well-defined market. In this case the price effects stem primarily from the lack of nearby alternative hospitals. Finally, the PVH/HCA and SCV/Mission Bay mergers illustrate that even modest price effects are unlikely when the hospitals are far apart and do not have service overlap; the latter price effect is essentially zero.

10. Conclusions

■ In option demand markets, intermediaries sell choice sets to downstream consumers. If the intermediary market is competitive, then the price paid by the end-user is determined by the bargaining position of the upstream suppliers: when the value to consumers of a choice set is greatly reduced when a given firm is removed, that firm commands a premium. We derive and implement a measure, WTP, that permits the computation of a seller's power in option demand markets. There are several potential applications of this measure. For example, one could assess the relative power of body shops in their negotiations with automotive insurance companies. Data on out-of-insurance repair purchases could be used to recover the underlying demand structure, and our methods could then be implemented to compute the WTP to include each body shop in the insurer's repair network. Another application might examine the power of trade workers (e.g., plumbers) relative to the general contractors who hire them, assuming the necessary consumer choice data are available.

Perhaps the most significant application is health care. Using data from the San Diego hospital market, we demonstrate that our measure of WTP is highly correlated with profits. We also offer three applications of the WTP measure, all of which pertain to merger analysis. During the consolidation wave of the 1990s, merging hospitals overwhelmingly prevailed when the DOJ or the FTC attempted to block a merger. The courts cited a number of reasons in finding for the defendants, but two arguments frequently surfaced: (1) the relevant geographic market is large, and (2) nonprofit hospitals serve the community and therefore will not exercise their market power even if they have it.

The claim that the relevant geographic market is large rests upon flow analyses (Elzinga and Hogarty, 1973) showing that a significant number of patients receive treatment outside of a narrowly defined market. As observers have commented, the fact that a substantial portion of, say, oncology patients travel long distances for care reveals nothing about a hospital's market power over, for example, expectant mothers who generally want to deliver in a nearby hospital (Werden, 1981, 1990). More generally, the fact that a patient at the interim stage is willing to travel a great distance to receive care in no way indicates that she did not, *ex ante*, place a high value on having one or more local hospitals available in her network.

Our approach obviates the need for flow analyses. The parameters from the logit demand estimation allow computation of WTP for each hospital. This measure, when converted to a dollar value through regression equation (11), provides a direct means to assess the SSNIP criterion for both defining markets and predicting the price effects of a merger. These predictions are at odds with those from ad hoc flow analyses. Indeed, more than 30% of Chula Vista residents receive treatment in a San Diego hospital; nevertheless, we predict that a three-way merger, and one of the possible two-way mergers, in Chula Vista would lead to substantial price increases.

Some final caveats apply to our present study. As noted earlier, we lack precise profit information. Further validation should be performed on better data. We only consider the profitability of unilateral deviations in price postmerger. We do not compute a new equilibrium, which would have to account for fixed costs, entry, exit, and other competitor reactions. Also, while our derivation and estimation of WTP is structural, our bargaining model is reduced form and does not consider a variety of complex bargaining interactions. For example, when two hospitals merge, our model assumes that the splitting parameter α remains constant. A more realistic model would allow this to vary. Finally, we rely heavily upon the assumption that demand is logit. More computationally intensive approaches would allow relaxation of this assumption.

Appendix A

■ **Correction of Town and Vistnes.** There are two problems with Town and Vistnes's (2001) pioneering treatment of using *ex ante* utility to develop a measure of market power in an option demand market. The first problem is that they use an incorrect expression to calculate *ex ante* utility given under the assumption of logit demand. Their expression for the *ex ante* utility of a type-*i* consumer is given by their equation (3), reproduced here in our notation,

$$W^{EA^*}(G, Y_i, \lambda_i) = \int_Z \ln \left\{ \sum_{g \in G} \exp[w(Z_i)U(H_g, Y_i, Z_i, \lambda_i)] \right\} f(Z_i \mid Y_i, \lambda_i) dZ_i,$$

where $w(Z_i)$ is the cost-based DRG weight for diagnosis Z_i. Comparison of this with our equations (4) and (7) shows that this is incorrect. If the intention was to use the DRG weights, then the correct expression for *ex ante* utility is

$$W^{EA}(G, Y_i, \lambda_i) = \int_Z w(Z_i) \ln \left\{ \sum_{g \in G} \exp[U(H_g, Y_i, Z_i, \lambda_i)] \right\} f(Z_i \mid Y_i, \lambda_i) dZ_i.$$

If, given a utility function $U(\cdot)$ and a set of weights $w(\cdot)$, both of these formulas were applied to a dataset of 20 hospitals and 10,000 consumers in order to compute for each individual his *ex ante* utility $W^{EA}(G, Y_i, \lambda_i)$ and his Town and Vistnes utility $W^{EA^*}(G, Y_i, \lambda_i)$, then the two resulting vectors of computed utilities would be different, though undoubtedly correlated. Nevertheless, $W^{EA}(G, Y_i, \lambda_i)$ must be used if the purpose is to show that *ex ante* utility is a useful construct for deriving a measure of market power in option demand markets.

The second difficulty lies with Town and Vistnes's equation (4), the regression equation that they use to estimate the empirical relationship between price and the incremental, aggregate, *ex ante* expected utility that a hospital adds to a network. They use a slightly more sophisticated bargaining model than we do; the key equation in their formulation is their equation (1):

$$B_j = \min[\pi_G - \pi_{G-j}, \pi_{N_I} - \pi_{G-j+m_h}],$$

where B_j is hospital j's bargaining power, π_G is the profit of the MCO for its actual network G that includes j, π_{G-j} is the profit of the MCO for the alternative network that excludes j, and π_{G-j+m_h} is the profit of the MCO under the alternative network that excludes j and substitutes hospital m_j, which is the hospital not previously in the network that best substitutes for j. Town and Vistnes assume that the profit the MCO earns is proportional to the *ex ante* aggregate utility that the network generates and that the price hospital j can secure is proportional to its bargaining power B_j. Therefore, aggregate *ex ante* utility for the actual network and the two alternative networks, denoted W_G^{EA}, W_{G-j}^{EA}, and $W_{G-j+m_j}^{EA}$ respectively, can be substituted into the formula for B_j. Town and Vistnes assert that this leads to their equation (4), whose parameters they estimate through a switching regression:

$$\ln P_{jG} = X_j'\beta + (1 - \alpha_j)\delta_1 \ln(W_{G-j}^{EA}) + \alpha_j \delta_2 \ln(W_{G-j+m_j}^{EA}) + \varepsilon_{jG},$$

where P_{jG} is the price hospital j receives from the network G and X_j is a vector of hospital j's characteristics. This equation is incorrect because it indicates that hospital j's ability to obtain a high price is driven by the level of *ex ante* utility j creates rather than the measure suggesed by their theory, the incremental *ex ante* utility that j contributes. Thus the equation that their theory suggests should be estimated is

$$\ln P_{jG} = X_j'\beta + (1 - \alpha_j)\delta_1 \ln(W_G^{EA} - W_{G-j}^{EA}) + \alpha_j \delta_2 \ln(W_G^{EA} - W_{G-j+m_j}^{EA}) + \varepsilon_{jG},$$

This is different from the previous equation, which is the one that they state they used.

Appendix B

■ **A simple theory of MCO competition.** Let there be M competitive MCOs that sell their services at cost. To see that this competition naturally leads each MCO to choose the network of the whole as its network, suppose several MCOs are competing for a contract to cover the employees of firm XY. Focus on MCO ℓ, which has an associated network G_ℓ. If it secures firm XY's contract, then in monetary terms the *ex ante* utility that the XY group gains is

$$W_\ell^{EA}(G_\ell) = \frac{N_{XY}}{\gamma} \int_{Y,Z,\lambda} V^{IU}(G_\ell, Y_i, Z_i, \lambda_i) f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i,$$

where N_{XY} is the number of people in the firm XY's group, $f(\cdot)$ is the density of group members' characteristics and locations, and the formula is just equation (8) from the article modified to be total utility (in monetary units) rather than *ex* *ante* WTP. Note from equation (4) that $V^{IU}(\cdot)$ is increasing with the size of G_ℓ and therefore $W_\ell^{EA}(G_\ell)$ is also increasing in the size of G_ℓ i.e., if $G'_\ell \subseteq G''_\ell$, then $W_\ell^{EA}(G'_\ell) \leq W_\ell^{EA}(G''_\ell)$.

The cost to ℓ of providing the coverage for firm XY is

$$C + \alpha \sum_{j \in G_\ell} \Delta W_j^{EA}(G_\ell) + K_\ell,$$

where C is the actual expected hospital costs of caring for the group members, the summation term is the surplus that the hospitals extract through the bargaining process, and K_ℓ represents the MCO's costs of administering the coverage. C is a constant that does not vary with the identity of the MCO or the composition of the network because we assume that $\Delta C_j(G_\ell) = 0$.

Firm XY wants to choose the MCO that results in the largest possible surplus for it and its employees. Given that the competitive environment forces MCO ℓ to sell its services at cost, the surplus that ℓ generates for firm XY is

$$T_\ell^{EA}(G_\ell) = W_\ell^{EA}(G_\ell) - \left[C + \alpha \sum_{j \in G_\ell} \Delta W_j^{EA}(G_\ell) + K_\ell \right].$$

The dominant strategy for MCO ℓ to follow in its efforts to secure the XY contract is therefore to maximize this surplus through minimizing its costs K_ℓ and picking that network G_ℓ that maximizes the difference $\Omega(G_\ell, \alpha) = W_\ell^{EA}(G_\ell) - \alpha \sum_{j \in G_\ell} \Delta W_j^{EA}(G_\ell)$.

We now show that MCO ℓ maximizes this difference by expanding its network to be the network of the whole, denoted G_ℓ^*. This has two steps. First we show that WTP for a particular hospital j is weakly decreasing in the size of the network. Pick a particular hospital j and observe that logit demand implies that its market share in every micromarket is weakly decreasing in network size: $s_j(G'_\ell, Y_i, Z_i, \lambda_i) \geq s_j(G''_\ell, Y_i, Z_i, \lambda_i)$ if $G'_\ell \subseteq G''_\ell$. Again recall equation (8), which is the formula for *ex ante* WTP in terms of market shares:

$$\Delta W_j^{EA}(G) = \frac{N_{XY}}{\gamma} \int_{Y,Z,\lambda} \ln \left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i)} \right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i.$$

This, together with the monotonicity of market shares, immediately implies that if $G'_\ell \subseteq G''_\ell$, then $\Delta W_j^{EA}(G'_\ell) \geq \Delta W_j^{EA}(G''_\ell)$. In particular, if G_ℓ^* denotes the network of the whole, then $\Delta W_j^{EA}(G'_\ell) \geq \Delta W_j^{EA}(G_\ell^*)$ for all networks G'_ℓ.

Second, we show that firm XY's surplus is weakly increasing in the size of the network, i.e., that $\Omega(G_\ell, \alpha)$ is weakly increasing in the size of the network. It is sufficient to show that

$$\Omega(G'_\ell, \alpha) \leq \Omega(G''_\ell, \alpha)$$

whenever $G'_\ell \subseteq G''_\ell$ and $G'_\ell = G''_\ell / k$, where the notation G''_ℓ / k denotes the network G''_ℓ with hospital k removed. Take the difference

$$\begin{aligned}
&\Omega(G''_\ell, \alpha) - \Omega(G'_\ell, \alpha) \\
&\quad = \left[W_\ell^{EA}(G''_\ell) - W_\ell^{EA}(G'_\ell) \right] + \alpha \left[\sum_{j \in G'_\ell} \Delta W_j^{EA}(G'_\ell) - \sum_{j \in G''_\ell} \Delta W_j^{EA}(G''_\ell) \right] \\
&\quad = \left[W_\ell^{EA}(G''_\ell) - W_\ell^{EA}(G''_\ell / k) \right] + \alpha \left[\sum_{j \in G''_\ell / k} \Delta W_j^{EA}(G''_\ell / k) - \sum_{j \in G''_\ell} \Delta W_j^{EA}(G''_\ell) \right] \\
&\quad = \left[W_\ell^{EA}(G''_\ell) - W_\ell^{EA}(G''_\ell / k) - \alpha \Delta W_k^{EA}(G''_\ell) \right] + \alpha \left[\sum_{j \in G''_\ell / k} \Delta W_j^{EA}(G''_\ell / k) - \sum_{j \in G''_\ell / k_\ell} \Delta W_j^{EA}(G''_\ell) \right] \\
&\quad = \left[W_\ell^{EA}(G''_\ell) - W_\ell^{EA}(G''_\ell / k) - \alpha \Delta W_k^{EA}(G''_\ell) \right] + \alpha \sum_{j \in G''_\ell / k} \left[\Delta W_j^{EA}(G''_\ell / k) - \Delta W_j^{EA}(G''_\ell) \right].
\end{aligned}$$

Note that $\alpha \sum_{j \in G''_\ell / k} (\Delta W_j^{EA}(G''_\ell / k) - \Delta W_j^{EA}(G''_\ell))$ is nonnegative because $\alpha \in (0, 1)$ and $\Delta W_j^{EA}(G_\ell)$ is both nonnegative and weakly decreasing in G_ℓ. Similarly, $W_\ell^{EA}(G''_\ell) - W_\ell^{EA}(G''/k) - \alpha \Delta W_k^{EA}(G''_\ell)$ is nonnegative because $\alpha \in (0, 1)$ and, by definition, $\Delta W_k^{EA}(G''_\ell) = W_\ell^{EA}(G''_\ell) - W_\ell^{EA}(G''/k)$. These two observations establish that $\Omega(G''_\ell, \alpha) - \Omega(G'_\ell, \alpha) \geq 0$ if $G'_\ell \subseteq G''_\ell$. Therefore the network of the whole G''_ℓ maximizes the difference $\Omega(G_\ell, \alpha)$, which establishes that the dominant strategy for MCO ℓ is to include every hospital in its network.

This is an intuitive result. Increasing network size increases the *ex ante* utility $W_\ell^{EA}(G_\ell)$ of consumers because they have more choices for their care. It also increases the competition between the hospitals, which directly decreases $\Delta W_j^{EA}(G_\ell)$. It therefore should come as no surprise that the difference $W_\ell^{EA}(G_\ell) - \alpha \sum_{j \in G_\ell} \Delta W_j^{EA}(G_\ell)$ is increasing in network size.

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