

Competition and Market Power in Option Demand Markets

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1. Introduction

Some important markets feature intermediaries who 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 to 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 prior to 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 car might require. Similarly, patients commit to a network of medical providers at the time they purchase their health insurance, but before they know their specific treatment needs. Non-insurance examples include manufacturers who sign long-term contracts with suppliers, which 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 knowing their needs fully, 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.

We study the power of suppliers in OD markets. We consider a single intermediary assembling a network of suppliers on behalf of many consumers, whose preferences are assumed to follow the model of logit demand. The task of the intermediary is to determine how much to pay each supplier. When the intermediary forms the network, it knows the distribution of consumer preferences and the distribution of possible states of the world, but not the upcoming realizations. Once the network is formed, consumers realize their demands, and select their preferred supplier from the network. To fit our model to insurance networks, we assume that consumers pay the same price regardless of which network seller they select. Thus, their selection of sellers depends on non-price attributes only. Because the intermediary knows the *ex ante* distribution of consumers' preferences, it can aggregate over all consumers and compute the *ex ante* value of adding a particular seller to the network.¹

We evaluate this framework using data from the market for inpatient hospital services in San Diego. We estimate a multinomial hospital choice model to identify the parameters of patients' logit demand functions. Based on these estimates, we compute the value that each hospital adds to a hypothetical managed care network. Given that the San Diego hospital market is not perfectly competitive and that hospitals and managed care organization (MCOs) negotiate the prices at which services are provided, we use a simple bargaining model to specify what proportion of its added value each hospital captures. We then regress our estimates of added value on each hospital's actual profits from daily hospital services. We find that—as the

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

bargaining model predicts—hospital profits from managed care patients are highly correlated with the *ex ante* added values they bring to the network. This allows us to estimate the extent to which a hospital is able to extract higher premiums from MCOs when it strengthens its bargaining position through, for example, a merger.

We use these estimates to investigate the effects of mergers on hospital prices. Our estimates of the bargaining model indicate that pairwise mergers among three geographically close hospitals in the southern part of San Diego would lead to price increases between 3.4% and 43.7%, holding costs constant. This is important because research on hospital merger efficiencies suggests that such mergers are unlikely to generate cost savings of more than a few percent.² Thus, our results suggest that mergers among neighboring San Diego hospitals, particularly in the suburbs, would lead to higher prices for consumers.

Antitrust implications.

This is an important finding. In the 1990s, The U.S antitrust agencies lost virtually every challenge to a hospital merger.³ The mergers we assess would almost surely be approved were the courts to define markets as they did in these cases. Our results therefore highlight the need for the courts to reform their methodology for evaluating mergers.

In most of the contested merger cases, the courts' rulings turned on geographic market definition. The courts generally accepted market definitions derived from methods Elzinga and Hogarty (E/H) (1973) introduced. E/H 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

² For example, see Connor et al. (1998) and Dranove and Lindrooth (2001).

³ Losses include Poplar Bluff, MO (FTC v. Tenet Healthcare Corp., E.D. MO 1998, reversed 8th Cir. July 1999); Joplin, MO (FTC v. Freeman Hospital, W.D. MO 1995); Long Island, NY (United States v. Long Island Jewish Medical Center, E.D. NY 1997); and Dubuque, IA (United States v. Mercy Health Services, N.D. Iowa 1995).

large market boundaries and, consequently, permissive merger rulings. Our results indicate that this may be a serious error. That some patients are willing to travel does not eliminate the market power hospitals may have in their local neighborhood. Many patients, especially those with diseases 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. Our empirical findings suggest that hospitals successfully translate these preferences into higher negotiated prices with MCOs.

We elaborate on our criticisms of the E/H approach in a companion paper, Capps et al. (2001). In that paper we calculate the effects of hospital mergers under the increasingly counterfactual assumption that the hospital services market is a direct purchase market—like restaurant meals or clothing. Although it appears ambiguous theoretically whether mergers in OD markets should confer more or less market power than do mergers in direct purchase markets, we find that the estimated price increases computed in Capps et al. under the assumption of direct purchase are in line with those computed here under the assumption of option demand. Perhaps not surprisingly, market power that stems from consumer loyalty seems to translate into higher prices irrespective of the specific market organization.

Related literature.

This paper relates both to the theoretical literature on common agency and the empirical literature on hospital pricing. Intermediation in option demand markets is an example of common agency. In a typical common agency problem, several principals contract with a single agent who exerts effort to sell the principals' services.⁴ 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

⁴ For example, see Bernheim and Whinston (1985, 1986).

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. We focus on the value each principal contributes to the agent's network and present a reduced form estimate of how the negotiation process splits this value between the principals and the agent. A related paper is Dranove and White's (1996) study of option demand. It examines pricing when sellers are committed to being in a single network, such as when a medical staff (the principals) agrees to offer its collective services to the patients of a particular hospital (the agent). That paper, unlike this paper, did not examine the implications of the intermediary being able to elect to include only a specific subset of sellers in the network.

There is also a substantial empirical literature on hospital pricing. One branch of this literature, including 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, including Staten, Umbeck, and Dunkelberg (1988) and Melnick et al. (1992) examines the hospital prices paid by specific health insurers. All of these studies use exogenous measures of market structure based on geographic delineations or patient flow analyses. For this reason, they are consistent with the traditional legal approach to assessing hospital mergers, in which the first step is to define the geographic market. The basis for this approach is traditional oligopoly theory (e.g. Cournot's model), in which there is a direct mapping from market structure (e.g. the Herfindahl index) to the market price. Despite the pervasiveness of this approach in the literature and in the courts, it is not appropriate for hospital markets because it fails to account for differentiation and substitution patterns across individual sellers. Nor does it account for the special characteristics of option demand markets. Indeed, the joint findings herein and in Capps et al. (2001) strongly

suggest that a court approach to assessing mergers based on the traditional structure-conduct-performance paradigm is inappropriate. The structural modeling approach that we describe herein appears better tailored to the specific institutional features of hospital markets.

Our paper is closely related to the highly original paper of Town and Vistnes (2001) and follows the same program that they followed: both use a logit demand model to estimate the value that individual hospitals add to a managed care network and measure how those values translate into the prices that hospitals negotiate with the MCOs. Our paper, however, differs from their work in four important ways. First, beginning with the random utility formulation that underlies the logit demand model, we derive a measure for the market power of each hospital. For a given hospital it is consumers' willingness to pay (WTP) to have that hospital retained in the MCO's network of participating hospitals. Town and Vistnes present a similar formula for market power, but do not present a derivation of it. Inspection of it against our derivation shows that it incorrectly aggregates consumers' expected utilities for different diagnoses into *ex ante* expected utility.⁵ Second, in implementing their formula to aggregate up to *ex ante* expected utility, they weight the interim utilities by the cost of treatment for that diagnosis. Equating value to cost is appropriate in a perfectly competitive market, but doing so in the imperfectly competitive market for hospital services is problematic. By contrast, under plausible assumptions, we are able to estimate weights for this aggregation from consumers' choice behavior, which presumably reflects their personal values better than the costs of treatment. Third, we do not incorporate into our demand estimation a fixed effect for each hospital as Town and Vistnes do. Instead, in our formulation, the differential attractiveness of hospitals comes from identifiable characteristics of the hospitals' services, organization, and resources.

⁵ See footnote 11 below for a precise statement of the difficulty.

Fourth, Town and Vistnes have the actual prices that two MCOs negotiated with hospitals. This allows them to explore how the MCOs tailored their networks and the prices that they paid to individual hospitals. We have no reliable price data, though we do have a reasonable measure of the profit each San Diego hospital earned from all managed care plans. We therefore can only compute each hospital's added value within the network of all San Diego hospitals. Overall though, the results of the two papers are consistent: the price (or profit) that a hospital can negotiate varies directly with its market power as measured by consumers' WTP for its inclusion in the network of providers.

2. A Model of Option Demand

The value of a seller in an option demand market.

To align our discussion of OD networks with our empirical application from health care, we refer throughout to consumers as patients, sellers (the principals) as hospitals, and the intermediary (the agent) as an MCO. Our goal is to calculate each consumer's *ex ante* willingness to pay (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. This is distinct from his interim WTP, which is his WTP contingent on knowing his medical needs, but before he explores specific treatment options. To compute his *ex ante* WTP, however, we must 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 only conceive of one circumstance in which he would choose j for his care: congestive heart failure requiring a heart transplant, for 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 In other words, given that during the next year he learns that he has congestive heart failure but has not yet decided at which hospital he will take treatment, he would pay \$60,000, if necessary, to have hospital j included in network G. By contrast, if consumer i should tear a ligament in his knee, then his interim WTP to have access to hospital j would be low, say \$10, because there are several closer, more convenient hospitals that could provide at least as good care as j. Finally if he remains healthy, then hospital j is of no use, and his interim WTP for access to j is \$0.

We can now translate interim WTP into *ex ante* WTP. Consumer i understands, happily, that his probability of remaining healthy for the next year is high, of injuring a knee ligament is low, and developing congestive heart failure is negligible. Therefore his *ex ante* WTP to have j included in the network might be only \$5; it is calculated as his interim WTP across all possible diagnoses (including healthy) weighted by each diagnosis's probability. The implication of this for hospital j is that 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 more likely, or 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

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

consumers. We next formalize these concepts, first by computing the interim utility of selecting a specific hospital, and then by computing the *ex ante* utility.

Interim utility.

Suppose the patient can choose one hospital from the set \mathbf{G} of network hospitals. The utility of patient i who has particular clinical characteristics and who has decided to utilize hospital j is

$$(1) \quad \begin{aligned} U_{ij} &= \alpha H_j^C + H_j' \Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} X_i + \tau_3 T_{ij} H_j^C - \gamma(X_i^C, X_i^S) P_j(X_i^S) + \varepsilon_{ij} \\ &= U(H_j, X_i, \lambda_i) - \gamma(X_i) P_j(X_i^S) + \varepsilon_{ij}. \end{aligned}$$

Here $H_j = \begin{bmatrix} H_j^C \\ H_j^S \end{bmatrix}'$ is a column vector of hospital characteristics where the variables in H_j^C are

features that are common across all patient conditions, such as teaching status. The variables in H_j^S are condition-specific service offerings such as whether a hospital has a delivery room. This structure implies that a particular hospital service only benefits patients whose diagnosis is related to that service. For instance, if patient i is admitted for a delivery, then the corresponding element in H_j^S is an indicator of the presence of a delivery room at hospital j .⁷ The vector

$X_i = \begin{bmatrix} X_i^C \\ X_i^S \end{bmatrix}$ includes both socioeconomic characteristics (X_i^C) and clinical attributes (X_i^S) of

patient i that affect what services he may need.⁸ $P_{ij} = P_j(X_i^S)$ is the out-of-pocket price that i ,

with clinical characteristics X_i^S , 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

⁷ In our empirical analysis, many elements of Γ , namely those corresponding to irrelevant service-diagnosis pairs, are constrained to be zero. For example, this restriction implies that cardiac patients, in choosing their hospital, do not consider whether a hospital has a delivery room.

⁸ Mnemonically, the C superscript stands for *characteristics* of the hospital or patient that are the same regardless of the patient's realized condition; the S denotes specific *services* offered by the hospital whose value depends on the patient's ailment.

j. The error term ε_{ij} represents that 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 (α), patient-specific values of hospital characteristics (the matrix Γ), travel costs (τ), and the value of money as a function of the patient's characteristics ($\gamma(X_i^C, X_i^S) > 0$). Note that hospital services, H_j^S , appears only via their interactions with patient characteristics, X_i .

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

$$\begin{aligned}
 & \alpha(H_j^C - H_k^C) + (H_j - H_k)' \Gamma X_i \\
 (2) \quad & + \tau_1(T_{ij} - T_{ik}) + \tau_2(T_{ij} - T_{ik})X_i + \tau_3(T_{ij}H_j^C - T_{ik}H_k^C) + \gamma(X_i^C, X_i^S)(P_j - P_i) \\
 & = U(H_j, X_i, \lambda_i) - U(H_k, X_i, \lambda_i) \\
 & > \varepsilon_{ik} - \varepsilon_{ij},
 \end{aligned}$$

where we assume: (i) that the ε_{ik} and ε_{ij} are distributed independently and identically with the standard double exponential distribution, and (ii) the term $\gamma(X_i^C, X_i^S)(P_j - P_i)$ drops out because the presence of health insurance implies that in our data there are no meaningful out-of-pocket price differences among hospitals. Assumption (i) implies that the probability that patient i chooses hospital j is given by the logit demand formula:

$$(3) \quad p_{ij} = \frac{\exp[U(H_j, X_i, \lambda_i)]}{\sum_{k=1}^J \exp[U(H_k, X_i, \lambda_i)]}.$$

If there are many patients with the same characteristics X_i and location λ_i as i, then p_{ij} can be thought of as hospital j's share of type i patients.

A major advantage of this specification is that the interaction of patient and hospital characteristics permits flexible substitution patterns across hospitals. As one hospital becomes

less attractive (say, because its travel time increases), different patients may react in different ways. Depending on their illness, income, location, and other characteristics, some may remain, others may go to another nearby hospital, while others may choose to travel further for care. This flexibility allows us to more precisely to estimate the demand facing each hospital and identify competitors.⁹ Estimation of (3) by maximum likelihood yields the underlying parameters of the utility function (1), with the exception of $\gamma(X_i^C, X_i^S)$.

Willingness to pay to include hospital j in a network.

We wish to compute patient i's *ex ante* WTP for the option to select hospital j from a given network of hospitals G. To do so, we first compute, for each possible vector of clinical indications X_i^S , the decrease in i's interim utility when j is removed from the network. Thus, given the expected utility specification in (1), i's interim expected utility (up to an arbitrary constant) for access to network G is¹⁰

$$(4) \quad \begin{aligned} V^{IU}(G, X_i^C, X_j^S, \lambda_i) &= E \max_{g \in G} [U(H_g, X_i^C, X_j^S, \lambda_i) + \varepsilon_{ig}] \\ &= \ln \left[\sum_{g \in G} \exp(U(H_g, X_i^C, X_j^S, \lambda_i)) \right]. \end{aligned}$$

Hospital j's contribution to this value is

$$(5) \quad \Delta V_j^{IU}(G, X_i^C, X_j^S, \lambda_i) = V^{IU}(G, X_i^C, X_j^S, \lambda_i) - V^{IU}(G/j, X_i^C, X_j^S, \lambda_i),$$

⁹ One concern about logit demand models is the specification of the outside option. As 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.

¹⁰ For a given choice set G, if each u_g is the systematic component of utility and each ε_g is independently distributed standard extreme value (i.e., standard double exponential), then $E \left[\max_{g \in G} (u_g + \varepsilon_g) \right] = \ln \left[\sum_{g \in G} \exp(u_g) \right]$.

where G/j is the network G with hospital j excluded. Converting this to monetary terms gives, conditional on his clinical indications X_i^S , patient i 's interim WTP to have hospital j be part of network G :

$$(6) \quad \Delta W_j^{IU}(G, X_i^C, X_j^S, \lambda_i) = \frac{\Delta V_j^{IU}(G, X_i^C, X_j^S, \lambda_i)}{\gamma(X_i^C, X_j^S)}.$$

Thus, if patient i 's clinical condition should turn out to be X_i^S , and given that he will choose the hospital in the network that maximizes expected utility, $\Delta W_j^{IU}(G, X_i^C, X_j^S, \lambda_i)$ is i 's WTP to have hospital j included in network G .

Let $f(X^C, X^S, \lambda)$ be the joint density of the demographics, locations, and clinical indications of all consumers who will be sufficiently ill at some point in the next year to cause them to be patients in one of the network hospitals and let $f(X^S | X_i^C, \lambda_i)$ be the conditional density of patient i 's clinical characteristics X^S if he has demographics (X_i^C, λ_i) . Given network G and patient i with demographics (X_i^C, λ_i) , i 's *ex-ante* WTP to include hospital j in G is¹¹

$$(7) \quad \begin{aligned} \Delta W_{ij}^{EA}(G, X_i^C, \lambda_i) &= \int_{X^S} \Delta W_j^{IU}(G, X_i^C, X^S, \lambda_i) f(X^S | X_i^C, \lambda_i) dX^S \\ &= \int_{X^S} \frac{\Delta V_j^{IU}(G, X_i^C, X^S, \lambda_i)}{\gamma(X_i^C, X^S)} f(X^S | X_i^C, \lambda_i) dX^S. \end{aligned}$$

¹¹ Town and Vistnes' expression for the *ex ante* utility of a type i consumer is given by their equation (3), rewritten here in our notation,

$$V^{EA}(G, X_i^C, X^S, \lambda_i) = \int_{X^S} \ln \left\{ \sum_{g \in G} \exp \left[w(X^S) U(H_g, X_i^C, X^S, \lambda_i) \right] \right\} f(X^S | X_i^C, \lambda_i) dX^S,$$

where $w(X^S)$ is the cost based DRG weight for diagnosis X^S . 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 would be

$$V^{EA}(G, X_i^C, X^S, \lambda_i) = \int_{X^S} w(X^S) \ln \left\{ \sum_{g \in G} \exp \left[U(H_g, X_i^C, X^S, \lambda_i) \right] \right\} f(X^S | X_i^C, \lambda_i) dX^S.$$

This latter expression implicitly assumes, referring to our (7), that $\gamma(X^C, X^S) \equiv \alpha/w(X^S)$ where α is an unidentified positive constant. Leaving aside the issue that $w(X^S)$ is cost based, not preference based, this is a strong, though not implausible, assumption on how the value of interim utility varies with the diagnosis.

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):

$$\begin{aligned}
 \Delta W_j^{EA}(G) &= N \int_{X^C, \lambda} \Delta W_j^{EA}(G, X^C, \lambda) f(X^C, X^S, \lambda_i) dX^C d\lambda \\
 (8) \qquad \qquad &= N \int_{X^C, X^S, \lambda} \frac{\Delta V_j^{IU}(G, X_i^C, X^S, \lambda_i)}{\gamma(X_i^C, X^S)} f(X^C, X^S, \lambda_i) dX^C dX^S d\lambda,
 \end{aligned}$$

where N is the expected number of patients.

The *ex ante* willingness to pay for N ill consumers, expressed formally in equation (8), equals the *ex ante* willingness to pay 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 type of consumer, whether ill or healthy. From an interim perspective, including hospital j in the network is good for some ill patients (who want to choose hospital j) but of no consequence for healthy patients. Therefore the changes in interim utilities for healthy consumers are identically zero and drop out of the weighted sum, leaving (8) as the aggregate willingness to pay for the population of all consumers in the managed care plan.

Bargaining between the hospital and the MCO over consumers' WTP.

MCOs—the intermediaries that assemble hospital networks for purchasers of managed care health insurance—typically negotiate with hospitals over prices as they create networks. They have strong incentives to be tough in this bargaining because firms, governments, and other organizations that purchase managed care insurance for their employees make their choices among competing plans in part on the basis of price. But most of these purchasers also care about the value that the network provides their employees. This gives a hospital with a favorable location and characteristics substantial countervailing power against any MCO that is trying to

negotiate a price at or near marginal costs.¹² 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 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 inclusion of j causes some patients to switch from hospitals in G that receive lower rates of reimbursement. Alternatively, if j is a relatively low priced 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.¹³ Inasmuch as hospital j will only accept a contract to provide care that at least covers its variable costs and given that it captures α proportion of the gains from trade, the contribution it earns towards fixed costs and profit from the managed care segment of its business is

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

¹² Gal-Or (1999) provides a theoretical treatment of a bilateral market power scenario similar to this one. Using a circular location model in which patients are differentiated *ex ante* in their preferences for insurers and *ex post* by their realized illness, she demonstrates that MCOs can use networks and exclusionary contracts to extract more favorable pricing from hospitals. In turn, hospitals can merge to extract higher payments from the MCO.

¹³ The cooperative, complete information Nash bargaining solution implies $\alpha = 0.5$. Brooks, Dor, and Wong (1997) provide a good discussion of bargaining models applied to hospital-insurer bargaining.

Though we call π_j “profit,” we emphasize that it is in fact refers to the contribution towards both fixed costs and profits. Our goal is to show that this predicted relationship exists clearly in the data of San Diego in 1991.

Adaptation of the model for estimation.

The initial task in making the model estimable is to convert (8),

$$\Delta W_j^{EA}(G) = N \int_{X^C, X^S, \lambda} \frac{\Delta V_j^{IU}(G, X_i^C, X^S, \lambda_i)}{\gamma(X_i^C, X^S)} f(X^C, X^S, \lambda_i) dX^C dX^S d\lambda,$$

the formula for the WTP for hospital j 's inclusion in the network G , into a form that has a direct parallel in the data. This has two steps. First, consider $\Delta V_j^{IU}(G, X_i^C, X^S, \lambda_i)$, which is the interim utility that hospital j contributes to a consumer with clinical indications X^S , demographics X^C , and location λ . This can be expressed, using a Taylor series approximation, in terms of the share of the market $s_j(G, X^C, X^S, \lambda)$ that hospital j has among consumers with characteristics (X^C, X^S, λ) :

$$(10) \quad \Delta V_j^{IU}(G, X^C, X^S, \lambda) \approx \frac{s_j(G, X^C, X^S, \lambda)}{1 - s_j(G, X^C, X^S, \lambda)}.$$

This important formula, which can be estimated from the available data, follows from (3) and is derived in the appendix. The second step is that we restrict the function $\gamma(\square)$ to be constant:

$\gamma(X_i^C, X^S) = \gamma_p$. Together (10) and the assumption $\gamma(\square)$ is constant imply that (8) can be

rewritten as

$$(11) \quad \begin{aligned} \overline{\Delta W_j^{EA}}(G) &\equiv \gamma_p \Delta W_j^{EA}(G) \\ &= N \int_{X^C, X^S, \lambda} \frac{s_j(G, X^C, X^S, \lambda_i)}{1 - s_j(G, X^C, X^S, \lambda_i)} f(X^C, X^S, \lambda_i) dX^C dX^S d\lambda, \end{aligned}$$

The lack of price variation in the data precludes identification of γ_p , so we are only able to calculate $\overline{\Delta W}_j^{EA}(G)$, which is $\Delta W_j^{EA}(G)$ up to the unidentified scale factor γ_p . Fortunately this is sufficient for our purposes.

The condition that $\gamma(\square)$ be constant is somewhat restrictive. However, it naturally arises if each patient chooses among the hospitals in G as if he obeyed the following time sequence.

- 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 if everything else is equal, i.e., ρ_{ijk} is the value of i 's loyalty to hospital j relative to hospital k .
- Sometime during the year patient i learns his clinical condition X_i^S .
- Patient i recovers the latent vector $\varepsilon_i = (\varepsilon_{i1}, \dots, \varepsilon_{iJ})$ of loyalty premiums and chooses among the hospitals in G on the basis of (2).

This sequence implies that (8) is the correct formula for aggregating the interim utilities for each clinical indication X_i^S into the overall WTP for a particular hospital j .

Equation (8) indicates that we can learn about WTP from disease-specific information about market shares. To gain intuition as to why such market share information informs us as to which clinical conditions X^S have a large value $\Delta V_j^{IU}(G, X_i^C, X^S, \lambda_i)$ and contribute most to $\Delta W_j^{EA}(G)$, consider an individual i who lives at location λ_i , has demographics X_i^C , and can choose between two hospitals, j and k . Both hospitals are quite convenient for him, but j has a reputation for higher quality than k . Suppose *interim*, before i recovers his vector ε , the

probability that i chooses j is 0.51 if he realizes diagnosis S_A (leading to clinical indications $X_i^{S_A}$) while the probability he chooses j is 0.95 if he realizes S_B , a much more serious condition than S_A . Therefore, for S_A , the random difference $\varepsilon_{ij} - \varepsilon_{ik}$ in his idiosyncratic preference terms, rather than the expected utility difference $U(H_k, X_i^C, X_i^{S_A}, \lambda_i) - U(H_k, X_i^C, X_i^{S_B}, \lambda_i)$, dominates i 's choice between hospitals j and k . In other words, the difference in the expected utilities that j and k offer for the diagnosis S_A is relatively small.

By contrast, for diagnosis S_B , the difference in expected utilities dominates the idiosyncratic difference $\varepsilon_{ij} - \varepsilon_{ik}$. For this diagnosis, the difference in the expected utilities j and k offer is relatively large. Inspection of (4) and (5) shows that this larger difference in expected utilities for S_B implies that $\Delta V_j^{IU}(G, X_i^C, X_i^{S_B}, \lambda_i)$ (the incremental interim utility j offers if S_B is realized), exceeds $\Delta V_j^{IU}(G, X_i^C, X_i^{S_A}, \lambda_i)$, (the incremental interim utility j offers if S_A is realized). That is, if hospital j has high market shares in certain diagnoses then consumers will have a high WTP for its inclusion, provided those diagnoses are not too rare.

We have data on each hospital j 's profits π_j from private-pay patients, the majority of whom are managed care patients. We also observe patients' choices of hospital, so we can compute $\overline{\Delta W}_j^{EA}(G)$ using (11). Thus, we are almost in position to estimate (9), the relationship between profits and the possible gains from trade that the hospital brings to the managed care market:

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

where u_j is a random error term. The primary difficulty is that we have no measure of $\Delta C_j(G)$, the change in MCO's costs caused by adding hospital j to the network. Creating such a measure

is a difficult exercise, for it would require not only knowing from our demand model where patients would reallocate themselves if j were not available in the network, but would also require information on the MCO's cost of treating each of those patients at their preferred alternative hospital other than j . We do not have sufficiently detailed cost data in order to do these computations with any degree of confidence. Consequently, we assume that the cost of treating a given condition is the same at all hospitals, which implies that $\Delta C_j(G) = 0$. The equation we estimate is then

$$(12) \quad \begin{aligned} \pi_j &= \frac{\alpha}{\gamma_P} \left(\overline{\Delta W_j^{EA}}(G) \right) + u_j \\ &= a \left(\overline{\Delta W_j^{EA}}(G) \right) + u_j \end{aligned}$$

where a is the coefficient on our measure, $\overline{\Delta W_j^{EA}}(G)$, of consumers' WTP for hospital j 's inclusion. Since we cannot separately identify α and γ_P , (12) gives a reduced form relationship between willingness to pay and profits. The coefficient a may be biased (downward in expectation) because data limitations force us to assume that $\Delta C_j(G) = 0$, which creates an errors in variables problem.¹⁴ In any case, the estimate of the coefficient a enables us to map changes in bargaining power—for example, as a result of a merger—into changes in hospital profits and prices.

¹⁴ Suppose we were able to construct measures for $\Delta C_j(G)$ and that our data contained substantially greater number of hospitals than is the case for San Diego in 1992. Then it would be possible to identify both α and a simple form of the function $\gamma(X_i^C, X^S)$. In particular, let the functional form for $\gamma(\square)$ be $\gamma(X_i^C, X^S) = \delta g(X_i^C, X^S; b)$ where δ is a scalar parameter and b is a short vector of parameters. Define

$$\begin{aligned} \overline{\Delta W_j^{EA}}(G) &\equiv \delta \Delta W_j^{EA}(G) \\ &= N \int_{X^C, X^S, \lambda} \frac{s_j(G, X^C, X^S, \lambda_i)}{g(X_i^C, X^S; b) [1 - s_j(G, X^C, X^S, \lambda_i)]} f(X^C, X^S, \lambda_i) dX^C dX^S d\lambda. \end{aligned}$$

The nonlinear equation to be estimated is then

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

We empirically evaluate our model as follows. First, we estimate the logit demand model (1) to obtain the parameters of each patient's utility function. Second, we use these parameter estimates to compute estimates $\hat{s}_j(G, X^C, X^S, \lambda)$ of each hospital's market share for each discrete cell of patient characteristics (X^C, X^S, λ) . These estimated shares are used in formula (11) to compute $\overline{\Delta W}_j^{EA}(G)$ for each hospital j .¹⁵ Third, we run the regression equation (12) to estimate the coefficient a . This coefficient is then used in Section 5 to compute the price and profit effects of mergers.

3. The Data

The primary data are a cross-section of San Diego area patients and hospitals taken from the California Office of Statewide Health Planning and Development (OSHPD) 1991 Patient Discharge Report and Financial Disclosure Report. We select San Diego because it is large enough to have geographic submarkets, but not too large to be computationally burdensome. We examine 22 short-term general hospitals that all admit a wide range of patients and insurance types. For these hospitals, we only consider patients insured by Medicare, Medicaid, Blue Cross/Blue Shield (BCBS), or Fee-For-Service (FFS), as price is unlikely to materially affect their hospital choice.¹⁶ Further, to make the choice model meaningful, we restrict the sample to

¹⁵ 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 only have a very few elements. Using the empirical shares will be, for some cells, quite noisy estimates of the underlying expected shares. This noise will cause violation of the assumption that underlies approximation (10) for $\Delta V_j^{IU}(G, X^C, X^S, \lambda)$. Using the estimated shares damps this noise and, if our choice model is good, approximates the true expected shares.

¹⁶ The vast majority of these patients pay essentially the same out-of-pocket price regardless of which hospital they select. Medicare patients pay a fixed deductible. Many indemnity patients make either no copayment or a copayment based on a predetermined fee schedule. We cannot completely rule out the possibility that price affects decision making, however. Medicare inpatients may have to return for outpatient care, for which out-of-pocket expenses may vary by provider. Some indemnity patients may have to make a small copayment that is based on a percentage of the hospital's charges.

non-emergency admissions. In total, for the 22 short-term general hospitals in San Diego, there are 70,929 such patients.

Table 1 lists the San Diego hospitals, as well as dummies indicating for-profit status, teaching status, and whether transplant services are offered. This table also lists each hospital's revenue per discharge net of discounts from daily hospital services and per discharge costs for daily hospital services.¹⁷ We use this information later to assess how well our measure of willingness to pay predicts hospital pricing and profitability.

Table 2 contains summary statistics for the hospitals used in the analysis; the column labeled "Type" indicates, for variables used in estimating equation (1), whether the variable is a general hospital characteristic (H^C) or measures a specific service offering (H^S). *Profit* and *Teach* are dummy variables indicating whether the hospital is privately owned 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 1990.¹⁸ *Equipment Intensity* is the dollar value of equipment, divided by patient days in 1990. The remaining variables are dummies indicating whether a hospital offers the listed service.

** TABLES 1 AND 2 ABOUT HERE**

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 racial categories white, black, and other. Severity is notoriously difficult to measure, so 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

¹⁷ Most inpatient services are classified as "Daily Hospital Services" (DHS). For example, DHS include medical/surgical acute, labor and delivery, and an intensive care unit.

¹⁸ We use 1990 patient days to avoid endogeneity bias.

knowledge, new to health services research. To compute *pcttravel*, we begin with the universe of patients living in rural California counties that have hospitals. We then compute, by diagnosis related group (DRG), the percent of patients who leave their county of residence to receive treatment. Presumably, patients are more likely to bypass their local hospital when their condition is severe and/or the required treatment is complex.

Lastly, we computed *timeij* and *distanceij*. These are the travel time and distance, respectively, from patient *i*'s home zip code centroid to hospital *j*'s street address. This is obviously more accurate than zip code centroid to zip code centroid distance measures used in other studies. We obtained *timeij* and *distanceij* by using the "driving directions calculator" on the Mapquest.com web page. This feature accounts for actual driving conditions, and considers turns, stoplights, and freeway travel.

** TABLE 3 ABOUT HERE **

4. Estimation and Results

The first step toward obtaining the measure of interest, aggregate willingness to pay, is to estimate the utility function in equation (1). The choice model includes five types of variables. First are hospital specific variables that are constant across all patient conditions (H_j^C), including ownership type, teaching status, a dummy for transplant services (indicating a "high tech" hospital), and measures of equipment and nursing intensity. Second, to measure variation in willingness to travel for different types of hospitals, are interactions of travel time with those same hospitals specific variables ($T_{ij}H_j^C$). The third set of variables, interactions between travel time and the patient-specific clinical and demographic variables listed in Table 3 ($T_{ij}X_i$), allows travel aversion to vary with patient type and condition.

Fourth and fifth are the interactions between hospital characteristics and patient characteristics, $[H_j^C, H_j^S]' \Gamma [X_i^C, X_i^S]$. These include two distinct types of interacted variables: interactions between both types of patient characteristics and the hospital characteristics ($H_j^C \Gamma_1 X_i$), and interactions between diagnosis dummies and hospital service offerings ($H_j^S \Gamma_2 X_i^S$).¹⁹ Examples of the former include interactions between race (in X^C) and for-profit status (in H^C) as well as interactions between severity (in X^S) and teaching status (in H^C). An example of the latter is an interaction between dummies for an obstetric admission (in X^S) and for whether the hospital has a dedicated labor and delivery room (in H^S). Similar ‘match’ interactions are included for cardiac admissions, respiratory admissions, MRIs and CAT scans, and neurological admissions.

The choice model is estimated via maximum likelihood, with a pseudo- R^2 of .3510. The coefficient tables are lengthy and are not presented here, but they are available from the authors upon request. For the current work, one important finding is that the coefficient on *travel time* is negative and highly significant. There were also many significant interactions between patient and hospital characteristics, suggestive of highly flexible substitution patterns.

We use our estimate of the utility function (1) to construct each hospital's contribution to aggregate *ex ante* expected utility. Specifically we use (11) to compute $\overline{\Delta W_j^{EA}}(G)$, the incremental contribution of each hospital, relative to the set G of all seventeen private San Diego hospitals. The five government hospitals are not included in this calculation because they admit a disproportionate number of uninsured patients, can use local taxing power to offset revenue

¹⁹ So if the k^{th} element of H_j is in H^S and the l^{th} element of X_i is in X^C then $\Gamma_{l,k}$ is constrained to be zero. For example, *income* is not interacted with a dummy indicating whether the hospital has psychiatric services (an element of H^S), but *income* is interacted with the dummy for teaching status (an element of H^C).

shortfalls, and therefore may use their market power in a different manner than we hypothesize for the private hospitals. We calculate $\overline{\Delta W}_j^{EA}(G)$ using only those patients identified as belonging to an HMO or PPO. In doing so, we assume that they have the same underlying utility functions as do the Medicare and FFS patients who were included in the logit estimation. We exclude Medicare and FFS patients because the market power that the *ex ante* WTP measures is not relevant to the revenues a hospital receives from Medicare patients, for whom the government fixes a rate, and for FFS patients, for whom insurers pay a posted, not negotiated, price. The resulting values of WTP are summarized in Table 4.

Ideally, we would calculate $\overline{\Delta W}_j^{EA}(H)$ for each hospital $j \in H$, for each MCO network. This would require detailed information about each network and its enrollees, which we do not have.²⁰ Instead, as stated above, we calculate $\overline{\Delta W}_j^{EA}(G)$ for each of the seventeen hospitals in the network, relative to the entire set of hospitals, G . This is acceptable for two reasons. First, as a practical matter, most MCO networks include virtually all hospitals. Second, ambiguity often exists as to what choice set $H \subset G$ is relevant for a consumer because during open enrollment periods he may be able to choose among several different MCO networks, each of which overlaps to some degree with every other one.

We now turn to the relationship between $\overline{\Delta W}_j^{EA}(G)$ —willingness to pay—and hospital profits. In previous research on market power, Conner, Feldman, and Dowd (1998) examine hospital revenues per patient. One problem with this approach is that revenues from outpatient services are included in total revenues. There are many substitutes for outpatient services, including physician and clinic services, so inclusion of outpatient revenue may muddy the

²⁰ Town and Vistnes (2001) do have this information for two MCO networks in Los Angeles and do calculate a measure of $\overline{\Delta W}_j^{EA}(H)$ for each one.

analysis. For this reason, we restrict our analysis to daily hospital services—e.g., medical/surgical acute, the maternity ward, and the intensive care unit—for which there are few if any outpatient substitutes. Conner, Feldman, and Dowd (1998) also include revenues from Medicare patients, for whom the effects of market power will be evident in quantities, not prices, because price is fixed. We therefore focus on profits from daily hospital services that are derived from privately insured patients.²¹

Equation (12) from above, $\pi_j = a \left(\overline{\Delta W}_j^{EA} (G) \right) + u_j$, specifies the expected relationship between hospitals' profits from DHS for private pay patients against MCO enrollees' WTP for each hospital. Figure 1 graphs each hospital's profits against our measure of enrollee's WTP and Table 5 reports the results of the corresponding regression: a strong, precisely estimated positive relationship exists between $\overline{\Delta W}_j^{EA} (G)$, our *ex ante* measure of bargaining power, and *ex-post* hospital profits.²² Each one-unit increase in WTP increases profits from MCOs by \$5933 (with a standard deviation of \$632). To interpret the magnitude of this effect, consider the best and worst nonprofit hospitals, as measured by WTP: Community Hospital of Chula Vista ($\overline{\Delta W}_j^{EA} (G) = 334$) and Sharp Memorial Hospital ($\overline{\Delta W}_j^{EA} (G) = 3,269$). For these two hospitals, the WTP difference of 2,935 generates a profit difference of \$17.4 million.²³ In the next section,

²¹ The hospital financial data identifies revenue and admissions from privately insured patients, 66% of whom are managed care patients. Cost data are not similarly disaggregated, so our best measure of profits from managed care sources is $\pi_{MCO} = R(Q_{Private})Q_{Private} - AC(Q)Q_{Private}$.

²² While the model in Section 2 implies a linear relation with no constant, if a log-log specification with a constant is estimated, then the coefficient on $\ln \left(\overline{\Delta W}_j^{EA} (G) \right)$ is 1.12 (.26) and the null hypothesis that the coefficient is one is not rejected. Thus another description of the relationship between WTP and profits is that the elasticity of profits with respect to WTP is unity.

²³ Recall that by "profit" we are referring to revenue above fixed costs. Also recall that we are able to measure $\overline{\Delta W}_j^{EA} (G)$ only up to an unidentified multiplicative constant.

we simulate the effects of mergers by mapping changes in WTP due to a merger into changes in profits and prices.

One recent hospital merger case²⁴ focused attention on possible differences between nonprofit and for-profit hospitals and their willingness to exploit market power, but inspection of Figure 1 does not immediately suggest a difference in the negotiating behavior of for-profit and nonprofit hospitals. To check for this possibility, we also estimated a version of the model that allowed the slope parameter, a , to vary by type of control:

$$\pi_j = a_1 \left(\overline{\Delta W}_j^{EA}(G) \right) + a_2 1_{[\text{for-profit}]} \bullet \left(\overline{\Delta W}_j^{EA}(G) \right) + u_j$$

where $1_{[.]}$ is the indicator function. The marginal effect of a unit of WTP is essentially unchanged ($\hat{a}_1=6,002.00$, s.d.=682.95), and there is no statistically significant difference by type of control in the relationship between profit and WTP ($\hat{a}_2=751.93$, s.d.=2,249.01).

To understand the sources of hospital pricing power and profitability, examine again equation (11),

$$\overline{\Delta W}_j^{EA}(G) = N \int_{X^C, X^S, \lambda} \frac{s_j(G, X^C, X^S, \lambda_i)}{1 - s_j(G, X^C, X^S, \lambda_i)} f(X^C, X^S, \lambda_i) dX^C dX^S d\lambda,$$

the formula for WTP. Think of each triple (X^C, X^S, λ) as specifying a distinct market segment of patients who all have demographic characteristics X^C , clinical indications X^S , and location λ . 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 j a high market share. To obtain a high share hospital j must have above average amounts of characteristics (H^C, H^S) that, within the utility function

²⁴ FTC v. Butterworth Health Corp., W.D. Michigan 1997.

(1), interact positively with the characteristics (X^C, X^S, λ) of the 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 very low values for $f(X^S, X^C, \lambda)$.

We can 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 462 DRGs in the data. The component for DRG X^S is defined to be

$$(13) \quad \overline{\Delta W}_j^{EA}(G, X^S) = N \int_{X^C, \lambda} \frac{s_j(G, X^C, X^S, \lambda_i)}{1 - s_j(G, X^C, X^S, \lambda_i)} f(X^C, X^S, \lambda_i) dX^C d\lambda$$

so that $\sum_{X^S} \overline{\Delta W}_j^{EA}(G, X^S) = \overline{\Delta W}_j^{EA}(G)$.²⁵

Now consider two dramatically different hospitals, the University of San Diego Hospital (UCSD) and Scripps 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 or be in a higher income area. We would expect, however, that the higher-quality UCSD generates relatively more of its total WTP from more severe DRGs. To demonstrate this, we compute the DRG-specific WTP components $\overline{\Delta W}_j^{EA}(G, X^S)$ for UCSD and SCV. Figure 2 shows these values for each hospital, with DRGs sorted by increasing severity (as measured by *pcttrv*). While UCSD is uniformly above SCV, meaning that for every DRG it generates more WTP by being in the choice set, the contribution gap begins to widen dramatically above the median severity DRG. This shows how a hospital,

²⁵ Note that the weighting by $f(X^S, X^C, \lambda)$ causes hospitals' values to tend to move together as the probability of contracting an ailment is independent of the hospital chosen upon contraction.

even if its overall market share is low, can gain leverage by successfully specializing in specific segments that are important to consumers because of their severity.

5. Simulating the Effects of Mergers on Hospital Profits

In general, market power after a merger increases because the merged entities can coordinate pricing in a manner that they could not pre-merger. The same principle applies here: two merged hospitals increase their market power by making their decision to join or refuse to join an MCO's network a joint decision in which either both join or both refuse. Consider two 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 Z 's network. Patients enrolled in Z may only have a small WTP for adding hospital k to the network because the included hospital j is an excellent substitute. Similarly, if it were that j was excluded and k included, then enrollee's WTP for j would also be small. Thus the sum, $\overline{\Delta W}_j^{EA}(G) + \overline{\Delta W}_k^{EA}(G)$, is small.

Now suppose j and k merge and inform MCO Z that it must include both j and k in its network if it wants either one. If Z excludes both j and k , then its enrollees' WTP for the bundle j and k is likely to be large because there is no good substitute that is at all convenient for them to use. Thus, more than likely, $\overline{\Delta W}_{j+k}^{EA}(G) \gg \overline{\Delta W}_j^{EA}(G) + \overline{\Delta W}_k^{EA}(G)$ where $\overline{\Delta W}_{j+k}^{EA}(G)$ denotes enrollees' WTP for the bundle of hospitals j and k . The formula for computing it is the straightforward generalization of (11):

$$(14) \quad \overline{\Delta W}_{j+k}^{EA}(G) = N \int_{X^C, X^S, \lambda} \frac{s_j(G, X^C, X^S, \lambda_i) + s_k(G, X^C, X^S, \lambda_i)}{1 - s_j(G, X^C, X^S, \lambda_i) - s_k(G, X^C, X^S, \lambda_i)} f(X^C, X^S, \lambda_i) dX^C dX^S d\lambda.$$

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, however, is incorrect because if two hospitals are far enough apart, then hospital j will have zero market share in each market segment (X^C, X^S, 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

$$(15) \quad \pi_{jk} = \hat{\alpha} \left[\overline{\Delta W_{j+k}^{EA}}(G) - \overline{\Delta W_j^{EA}}(G) - \overline{\Delta W_k^{EA}}(G) \right]$$

where $\hat{\alpha}$ is the coefficient on WTP from the regression in Table 5. It takes the empirically observed relationship between WTP and profits in San Diego and uses it to project how much a merger-driven increment to WTP would permit the combined hospitals to increase their profits.

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. We consider this suburb because it bears directly upon a key issue in many hospital merger cases. Due to its high patient outflows (around 30%) and proximity to San Diego, Chula Vista is clearly no less competitive than the markets where the FTC challenged mergers and lost. Thus, if our calculations indicate that mergers in Chula Vista are anti-competitive, then perhaps the same could be said for those other markets.

Table 6 reports the results of simulating the effects of mergers among the three Chula Vista Hospitals. They indicate that most mergers in this suburb would lead to significant

increases in profits. Should all three hospitals merge, the estimated effect on profits is an increase of 37.6%. Depending on the hospitals involved, pairwise mergers would lead to increases in profits of 4.3%, 7.3%, and 31.2%.²⁶ Note that these increases in profit are due to the enhanced bargaining power of the hospitals against the MCOs and are a direct transfer from MCOs and their members to the hospitals.

***** TABLE 6 ABOUT HERE*****

Antitrust policy is generally concerned with prices rather than profits. The bottom panel of Table 6 shows the increase in the average revenue (price) of an inpatient day, under the assumption that quantity is unchanged.²⁷ These price changes reflect the increases in average revenue necessary to generate the predicted increase in profits, given the pre-merger number of patients, average revenue, and average cost at each hospital. The predicted increase for a three-way merger is 40.0%, while pairwise mergers generate price increases ranging from 3.4% to 43.4%. In the merger with the smallest predicted effect, CHCV and Paradise, the price increase appears to be attenuated for two reasons: Scripps lies directly between CHCV and Paradise, and CHCV does not have labor and delivery services. Overall, these increases are well above the levels most policy makers deem acceptable—the average price of inpatient stay in San Diego in 1991 was \$2994, so a 7.4% price increase (Scripps and CHCV) corresponds to an increase of \$222 per admission. Realization of cost savings large enough to offset these market power effects is unlikely. For example, Connor et al. (1998) find that hospital mergers are unlikely to

²⁶ These profit increases compare post-merger profits with the sum of merging hospitals' pre-merger profits.

²⁷ 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 the calculations in Table 6 would under-predicts the price increase.

produce savings of more than 3-4 percent. Dranove and Lindrooth (2001) use a pseudo natural experiment approach and find similarly small savings for mergers, and no savings for systems.²⁸

For comparison, Table 7 shows the results of simulating the effects of six other potential mergers. The first merger, between Sharp Memorial and UCSD, involves two hospitals near downtown San Diego, roughly five miles apart. The price increase of 10.3% reflects a combination of service overlap—both are teaching hospitals offering labor and delivery—and geographic proximity. The Scripps/Paradise merger described above involved similar service overlaps and distance, but has a much larger predicted price increase. The difference between the two is that Sharp and UCSD are located near several other downtown hospitals whereas Scripps and Paradise have just one nearby rival. The second simulation is for a pair of hospitals located in La Jolla, a neighborhood 11 miles north of downtown San Diego. A merger of Scripps of La Jolla and HCA has a predicted price increase of 15%, in spite of the lack of service overlap. In this case the price-effects stem primarily from the lack of nearby alternative hospitals.

***** TABLE 7 ABOUT HERE*****

Comparing the San Miguel/Mercy merger to the Sharp Memorial/UCSD merger highlights the important role of service overlap and nearby rivals. Because they do not have significant services overlap and also have multiple rivals less than five miles distant, a merger of San Miguel and Mercy hospitals is predicted to increase prices by just 2.9%, in spite of the fact that they are only 1.2 miles apart from each other. The Paradise/HCA and SCV/Mission Bay mergers illustrate that mergers are unlikely to lead to large price effects when the hospitals are both far apart and do not have extensive service overlap.

²⁸ In a system, hospitals consolidate ownership but retain individual licenses for regulatory purposes.

Determinants of the Increased Market Power from Merger

Although our methods can be implemented using data that is readily available for most states, they are admittedly more cumbersome than a simple analysis of patient flows. Thus, hospitals and antitrust enforcers seeking to rapidly assess the competitive implications of a merger may seek simpler methods that rely on easily observed features of the proposed merger. To offer the desired “shortcut”, we used equation (11) to compute the market power gains from each of 120 hypothetical “one-on-one” mergers in San Diego, and regressed these computed gains on various measures of geographic, demographic, and services overlap. We do not report the regression result here, but offer a review of our findings. Having one teaching hospital in a merger, *ceteris paribus*, increases the gains from merger by roughly \$500,000; a merger between two teaching hospitals increases the gain by a further \$1,000,000. Mergers among hospitals in markets with widely divergent levels of patient incomes appear less profitable, suggesting that hospitals have more to gain when they serve a similar patient demographic.²⁹ Mergers among downtown hospitals are also less profitable, likely because there are many nearby competitors. Surprisingly, mergers between hospitals offering similar services generally do not increase WTP significantly, with the exception of labor and delivery services.

Comparison with Merger Effects in Direct Purchase Markets.

Intuition suggests that market power should be related in traditional and option demand markets. In an OD setting, a given hospital has market power to the extent that the *ex ante* expected utility of consumers' choice set is significantly lower when that hospital is excluded

²⁹ The driving time between the merging hospital appears to be close to collinear with the hospitals' income difference, with a correlation of 0.61. When both variables are included, the coefficient on *incdif* is more negative (-0.81 vs. -0.55), while *time* is positive and insignificant (0.21, $t=1.51$), and the joint effect is negative and significant (-0.6, $t=-1.99$).

from the network. But a hospital's contribution to *ex ante* WTP is high only if, for some substantial subset of patients, it provides substantial interim WTP.

In a direct purchase market—e.g., fee-for-service without insurance—the consumer chooses his hospital, taking price into account, after he learns his diagnosis. When making this choice, the consumer considers his diagnosis, the characteristics of alternative hospitals, and the prices they will charge him. Roughly speaking, a hospital is able charge the consumer a high price in this situation only if the alternative hospitals provide significantly less interim utility whenever they do not have a price advantage. The ability to provide superior interim utility to a subset of consumers is the same basic source of market power that hospitals exploit in OD markets. This correspondence is only suggestive, however, because, for example, the individual hospital's price elasticity of demand does not appear explicitly in the option demand setting.

Given this intuition, the results that Capps et al. (2001) report in a companion paper are not surprising. That paper also studies competition in the San Diego hospital market, but uses a traditional approach in which hospitals are modeled as setting a different price for each insurer-DRG pair with no *ex ante* payments. Such a framework best fits the rapidly shrinking fee-for-service market in which private insurers pay posted prices for the services that their policy holders use. They use two distinct approaches to analyze the effects of mergers among Chula Vista hospitals. Both approaches find that pairwise mergers would increase prices by 5% to 9%. The corresponding increases for the option demand case (from Table 6) are between 3.4% and 43.4%. Thus, while the values vary with the pricing model, both analyses indicate that hospitals in Chula Vista do indeed have market power and that mergers would be anticompetitive. This is in spite of the high outflows of Chula Vista residents to hospitals in San Diego.

6. Conclusions

In option demand markets, intermediaries essentially 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 supplier: when the value to consumers of a choice set is greatly reduced when one firm is removed, that firm commands a premium. Such a model applies to a number of markets, but perhaps the most significant one is health care—a market now accounting for about 14% of GDP. Costs of care are already rising due to exogenous technological change and the aging of the population; overly liberal antitrust enforcement will only exacerbate this.

During the consolidation wave of the 1990s, merging hospitals overwhelmingly prevailed when the DOJ or the FTC attempted to block a merger.³⁰ The courts cited a number of reasons in finding for the defendants, but several arguments frequently appear: (1) the relevant geographic market is large, (2) nonprofit hospitals serve the community and therefore will not exercise their market power even if they have it, and (3) MCOs significantly restrain the pricing power of hospitals. Our work casts significant doubt on each of the claims.

The claim that the relevant geographic market is large rests upon flow analyses (Elzinga and Hogarty 1972, 1974) showing that a significant number of patients receive treatment outside of a narrowly defined market. Numerous papers have identified many flaws in E/H style analyses, not the least of which is that it is not grounded in theory. For example, Capps et al. (2001) note that the fact that some patients do travel reveals nothing about hospital pricing with respect to those who do not.³¹ Moreover, the *ex ante* nature of pricing in an option demand setting renders the connection between consumer flows and pricing power is even more tenuous:

³⁰ See note 3.

³¹ See also Werden (1981, 1989).

ex-post, at the interim stage, some unlucky patients may suffer an ailment for which they are willing to travel a great distance to receive care. This in no way indicates that they did not, *ex ante*, place a high value on having one or more local hospitals in their network. Indeed, more than 30% of Chula Vista residents receive treatment in a San Diego hospital; nevertheless we predict that a merger in Chula Vista would lead to substantial price increases.³² Our structural approach obviates the need for flow analyses; indeed, it obviates the need to debate over the relevant market. The parameters of the logit demand estimation, combined with equation (11), provide a direct way to assess the market power implications of a merger.

The claim that nonprofit hospitals will not exercise market power remains the subject of considerable debate. Lynk (1995) adopts a reduced form structure-conduct-performance approach and finds that nonprofits price lower than for profit hospitals. Subsequent work by Dranove and Ludwick (1998) and Keeler et al. (1999) questions the robustness of this finding. Our empirical work finds no significant difference between the willingness of for-profit and nonprofit hospitals to exploit their market power.

Finally, the claim that MCOs can restrain hospital pricing does not, by itself, negate the ability of hospitals to exercise market power. Our analysis shows that to the extent that MCOs choose networks to meet the wishes of their enrollees, merging hospitals can enhance their market power vis-à-vis MCOs, and secure more favorable negotiated prices.

³² The Antitrust Agencies have long tried to persuade the courts to adopt the ‘small but significant and non-transitory increase in price’ (SSNIP) criterion for defining markets. Under this, a market is initially defined narrowly and if the included firms can implement a SSNIP then that is the appropriate geographic market. If they could not implement a SSNIP then it must be the case that a relevant competitor is not included in the proposed market definition, and thus it should be expanded. Clearly, under the SSNIP criterion Chula Vista is the relevant market. Moreover, this approach is more suitable for consideration of the welfare effects of a merger—flow analysis give concrete predictions about price only under very stylized circumstances.

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Appendix

To be computable from the data (8) must be expressed in terms of market shares. To do this, begin with (3) and let $z_j(X_i, \lambda_i) = \exp[U(H_j, X_i, \lambda_i)]$ so hospital j 's market share of type (X_i, λ_i) patients is

$$(A.1) \quad s_j \equiv s_j(G, X_i, \lambda_i) = z_j(X_i, \lambda_i) / \sum_{k \in G} z_k(X_i, \lambda_i).$$

Divide both sides of equation (A.1) by s_1 to derive

$$(A.2) \quad z_j(X_i, \lambda_i) = \frac{s_j}{s_1} z_1(X_i, \lambda_i).$$

Now, (4) can be re-written in terms of market shares and the expected utility of selecting hospital 1 as

$$(A.3) \quad \begin{aligned} V^{IU}(G, X_i^C, X_i^S, \lambda_i) &= \ln \left[\sum_{g \in G} z_g \right] = \ln \sum_{g \in G} \frac{s_g}{s_1} z_1 = \ln z_1 + \ln \sum_{g \in G} \frac{s_g}{s_1} \\ &= U(H_1, X_i^C, X_i^S, \lambda_i) + \ln \sum_{g \in G} \frac{s_g}{s_1}. \end{aligned}$$

The next step is to evaluate hospital j 's incremental contribution to patient i 's interim utility: $\Delta V_j^{IU} = V^{IU}(G, X_i, \lambda_i) - V^{IU}(G/j, X_i, \lambda_i)$ where G/j is network G with hospital j excluded. We approximate this by taking a first order Taylor approximation of V^{IU} around $x_0 = \sum_{g \in G/1} s_g/s_1$ as follows:³³

$$(A.4) \quad \ln \left[\sum_{g \in G} \frac{s_g}{s_1} \right] \approx \ln \left[\sum_{g \in G/k} \frac{s_g}{s_1} \right] + \frac{s_j}{1 - s_j}.$$

Equation (A.4) implies that hospital j 's incremental interim contribution to a patient with characteristics X_i is

$$(A.5) \quad \begin{aligned} \Delta V_j^{IU}(G, X_i^C, X_i^S, \lambda_i) &= V^{IU}(G, X_i^C, X_i^S, \lambda_i) - V^{IU}(G/j, X_i^C, X_i^S, \lambda_i) \\ &= \ln \left[\sum_{g \in G} \frac{s_g}{s_1} \right] - \ln \left[\sum_{g \in G/j} \frac{\tilde{s}_g}{\tilde{s}_1} \right] \\ &\approx \ln \left[\sum_{g \in G/j} \frac{s_g}{s_1} \right] + \frac{s_j}{1 - s_j} - \ln \left[\sum_{g \in G/j} \frac{\tilde{s}_g}{\tilde{s}_1} \right], \end{aligned}$$

where \tilde{s}_g denotes the share of hospital g among patients of type $(X_i^C, X_i^S, \lambda_i)$ when the choice set is restricted to the network G/j . Finally, the independence of irrelevant alternatives (IIA) property of the logit model implies that $s_g/s_1 = \tilde{s}_g/\tilde{s}_1$, which yields (10) in the text:

$$(A.6) \quad \Delta V_j^{IU}(G, X_i^C, X_i^S, \lambda_i, P(X_i^S)) \approx \frac{s_j}{1 - s_j}.$$

³³ This approximation is good only if $s_j \ll 0.5$, which is satisfied in our data: 95% of the s_{ij} terms are below 0.2 and 90% are below 0.125.

Table 1: San Diego Hospitals (N=22)	Patients in Sample	Control	Govt.	Teach	Transplants	Avg. Rev. per Discharge, DHS (net of deductions)	Average Cost, DHS Operating Expenses
HARBOR VIEW HEALTH PARTNERS	1,810	FP	N	N	N	\$3,064.49	\$1,485.74
HCA HOSPITAL OF SAN DIEGO, INC.	3,242	FP	N	Y	Y	\$3,126.00	\$1,675.04
MISSION BAY MEMORIAL HOSPITAL	905	FP	N	N	N	\$2,514.91	\$1,845.61
NME HOSPITALS, INC.	3,222	FP	N	N	N	\$3,452.25	\$1,435.86
CHILDREN'S HOSPITAL, SAN DIEGO	3,648	NFP	N	Y	N	\$5,429.09	\$2,594.56
COMMUNITY HOSPITAL, CHULA VISTA	1,561	NFP	N	N	N	\$3,458.28	\$1,910.83
CORONADO HOSPITAL, INC.	772	NFP	N	N	Y	\$2,543.68	\$1,328.10
FALLBROOK HOSPITAL DISTRICT	629	NFP	Y	N	N	\$1,157.93	\$681.63
GROSSMONT DISTRICT HOSPITAL	5,335	NFP	Y	N	N	\$2,487.94	\$1,186.91
MERCY HOSPITAL	7,994	NFP	N	Y	N	\$2,810.97	\$1,078.37
PALOMAR POMERADO, ESCONDIDO	4,799	NFP	Y	N	N	\$3,038.71	\$1,239.99
PALOMAR POMERADO, POWAY	2,358	NFP	Y	N	N	\$2,072.19	\$1,103.91
PARADISE VALLEY HOSPITAL	2,604	NFP	N	N	Y	\$2,308.95	\$1,091.12
SAN MIGUEL HOSPITAL	376	NFP	N	Y	N	\$4,310.31	\$1,573.53
SCRIPPS MEMORIAL HOSPITAL	800	NFP	N	N	N	\$3,252.65	\$1,516.35
SCRIPPS MEMORIAL, CHULA VISTA	4,137	NFP	N	N	N	\$1,714.70	\$730.46
SCRIPPS MEMORIAL, LA JOLLA	3,829	NFP	N	N	N	\$2,793.87	\$1,568.68
SHARP CABRILLO HOSPITAL	1,419	NFP	N	N	N	\$3,170.59	\$1,617.25
SHARP MEMORIAL HOSPITAL	10,620	NFP	N	N	Y	\$2,452.41	\$1,184.00
TRI-CITY HOSPITAL DISTRICT	5,172	NFP	Y	N	Y	\$2,121.46	\$1,008.51
UCSD MEDICAL CENTER	4,887	NFP	N	Y	Y	\$3,904.88	\$1,610.49
VILLA VIEW COMMUNITY HOSPITAL	550	NFP	N	N	N	\$4,683.88	\$1,665.34

Variable	Type	Mean	Std. Dev.	Min	Max
For Profit	H ^C	0.182	0.395	0	1
Teaching	H ^C	0.227	0.429	0	1
FTE Nurses per Patient Day	H ^C	5.582	1.420	3.503	9.096
Equipment per Patient Day, \$1000's	H ^C	0.343	0.118	0.069	0.573
Transplant Services	H ^C	0.273	0.456	0	1
Cardiac Clinic	H ^S	0.182	0.395	0	1
Neurological Intensive Care	H ^S	0.364	0.492	0	1
Pulmonary Intensive Care	H ^S	0.727	0.456	0	1
Psychiatric	H ^S	0.409	0.503	0	1
Computed Tomography	H ^S	0.864	0.351	0	1
Magnetic Resonance Imaging	H ^S	0.409	0.503	0	1
Labor/Delivery Room	H ^S	0.591	0.503	0	1
Open Heart Surgery	--	0.455	0.510	0	1
Chest Medical Clinic	--	0.136	0.351	0	1
Neonatal Intensive Care	--	0.500	0.512	0	1
Cardiac Catheterization	--	0.500	0.512	0	1
Neurosurgery	--	0.818	0.395	0	1
Alternative Birthing Center	--	0.455	0.510	0	1
Newborn Nursery Care	--	0.591	0.503	0	1
Premature Nursery Care	--	0.591	0.503	0	1
Skilled Nursing	--	0.455	0.510	0	1
Electroencephalography	--	0.818	0.395	0	1
Electromyography	--	0.636	0.492	0	1
X-Ray Therapy	--	0.455	0.510	0	1
Radioisotope Therapy	--	0.545	0.510	0	1
Emergency Room	--	0.818	0.395	0	1
Peripheral Vascular Lab	--	0.409	0.503	0	1
Average Revenue, DHS	--	\$2,994	\$976.85	\$1,158	\$5,429
Average Cost, DHS	--	\$1,415	\$421	\$682	\$2,595
Profit, Daily Hospital Services \$1000s	--	\$17,212	\$14,475	\$2107	\$55,235

Table 3: Patient Variables (N=70,669)					
Variable	Type	Mean	Std. Dev.	Min	Max
Male	X ^C	0.291	0.454	0	1
Over 60	X ^C	0.313	0.464	0	1
White	X ^C	0.662	0.473	0	1
Income, \$1000's	X ^C	14.802	6.463	0	40.27
Expected Length of Stay	X ^C	5.311	7.271	0	415
%Travel (<i>pcttrv</i>)	X ^C	0.211	0.056	0.13	0.58
Other Procedures	X ^C	1.434	1.372	0	4
Other Diagnoses	X ^C	2.135	1.438	0	4
Driving Time (minutes to chosen hospital)	--	15.566	10.029	1	79
Travel Distance (miles to chosen hospital)	--	8.694	7.502	0.3	61.1
Driving Time (minutes to all hospitals)	--	29.514	16.815	1	92
Travel Distance (miles to all hospitals)	--	19.964	13.823	0.2	69.3
Medicare Dummy	X ^C	0.273	0.446	0	1
Medical Dummy	X ^C	0.302	0.459	0	1
Blue Cross/Blue Shield Dummy	X ^C	0.027	0.161	0	1
Fee-For-Service Dummy	X ^C	0.120	0.325	0	1
HMO/PPO Dummy	X ^C	0.279	0.448	0	1
Neurological Diagnosis	X ^S	0.029	0.169	0	1
Respiratory Diagnosis	X ^S	0.036	0.186	0	1
Cardiac Diagnosis	X ^S	0.105	0.306	0	1
Labor/Delivery	X ^S	0.365	0.482	0	1
MRI/CT Admission	X ^S	0.045	0.208	0	1
Psychiatric Admission	X ^S	0.026	0.160	0	1

Table 4: Aggregate Willingness to Pay to Include each Hospital in the Choice Set (Up to a Constant)				
Hospital	Control	WTP, MCO Patients ($\overline{\Delta W_j^{EA}}$)	DHS Profit, Private Pay Patients (\$1000s)	
SHARP MEMORIAL HOSPITAL	NFP	3268.97	\$22,584	
UCSD MEDICAL CENTER	NFP	2717.15	\$22,863	
SCRIPPS - LA JOLLA	NFP	2610.08	\$13,654	
MERCY HOSPITAL	NFP	2484.61	\$18,886	
PARADISE VALLEY HOSPITAL	NFP	2073.67	\$3,343	
SCRIPPS - CHULA VISTA	NFP	1697.37	\$5,580	
NME HOSPITALS	FP	1659.23	\$8,742	
CORONADO HOSPITAL	NFP	1376.99	\$1,589	
HCA HOSPITAL OF SAN DIEGO	FP	1111.38	\$6,565	
CHILDREN'S HOSPITAL	NFP	1097.58	\$13,987	
SAN MIGUEL HOSPITAL	NFP	778.25	\$1,107	
SCRIPPS MEMORIAL	NFP	760.74	\$3,290	
VILLA VIEW COMMUNITY	NFP	595.23	\$756	
HARBOR VIEW HEALTH	FP	542.95	\$1,646	
SHARP CABRILLO	NFP	523.56	\$4,484	
COMMUNITY, CHULA VISTA	NFP	333.90	\$3,111	
MISSION BAY MEMORIAL	FP	333.85	\$1,127	
Variable	Mean	Std. Dev.	Min	Max
WTP, MCO Patients	1409.74	931.08	333.85	3268.97
DHS Profit, All Patients	\$16,690	\$15,174	\$2,582	\$55,254
DHS Profit, Private-Pay Patients	\$7,842	\$7,652	\$756	\$22,863

Table 5: Profit from Daily Hospital Services and WTP (N=17)
DHS Profit = 5932.664 • WTP (632.38)
$R^2 = .8462$
$\bar{R}^2 = .8366$
* Significant at 1% Level

Table 6: Merger Simulations for Chula Vista							
Joint Incremental Contributions to Ex-ante WTP							
	$\overline{\Delta W}_j^{EA}$	$\overline{\Delta W}_{j+k}(G)$			$\overline{\Delta W}_{j+k+1}(G)$		
	Alone	w/Scripps	w/Paradise	w/CHCV	All Three	Profit from DHS (\$1000s)	
Scripps	2073.67	**	4949.01	2180.15	5648.25	\$10,070	
Paradise	1697.37		**	2511.81	5648.25	\$12,302	
CHCV	333.90			**	5648.25	\$1,981	
Percent Increases in Joint Profits							
		w/Scripps	w/Paradise	w/CHCV	All Three		
Scripps		**	31.24%	7.33%	37.60%		
Paradise			**	4.33%	37.60%		
CHCV				**	37.60%		
Percent Price Increase Relative to Pre-Merger Patient-Weighted Average Price							
		w/Scripps	w/Paradise	w/CHCV	All Three		
Scripps		**	43.65%	7.36%	39.91%		
Paradise			**	3.37%	39.91%		
CHCV				**	39.91%		
Pre-Merger Patient-Weighted Average Price							
		w/Scripps	w/Paradise	w/CHCV	All Three	AR	Qty
Scripps		**	\$1,797	\$1,902	\$2,079	\$1465	6618
Paradise			**	\$3,000	\$2,079	\$2754	2293
CHCV				**	\$2,079	\$3265	2123

Table 7: Other Mergers									
Merging Hospitals	Gain in WTP	% Increase Profit	Pre-Merger Price	Post-Merger Price	% Increase Price	Miles (Minutes)	# Teaching	# Trans-plant	# Delivery
Sharp Memorial and UCSD ¹	1437.24	24.01%	\$3,274	\$3,612	10.33%	5.2 (10)	1	2	2
Scripps La Jolla And HCA ²	514.34	27.47%	\$3,223	\$3,705	14.98%	1.5 (3)	1	1	1
San Miguel And Mercy ³	155.99	4.78%	\$3,033	\$3,120	2.86%	1.2 (3)	2	0	1
Paradise And HCA ⁴	92.38	2.90%	\$3102	\$3182	2.67%	19.6 (26)	1	2	1
Villa View and Coronado ⁵	57.87	2.93%	\$2,070	\$2,228	7.63%	9.9 (22)	0	1	1
Scripps Chula Vista and Mission Bay ⁶	19.08	0.94%	\$1,641	\$1,655	0.81%	16.4 (23)	0	0	1

1. Sharp Memorial and UCSD are near downtown San Diego.
2. Scripps La Jolla and HCA are the only two hospitals in La Jolla, a northern suburb.
3. San Miguel and Mercy are both near downtown San Diego.
4. Paradise and HCA are on opposite sides of downtown San Diego.
5. Villa View is in Northeast San Diego and Coronado is near Downtown.
6. Scripps and Mission Bay are on opposite sides of downtown San Diego.

Figure 1: DHS Profit (Private-Pay Patients) & WTP (MCO Patients)

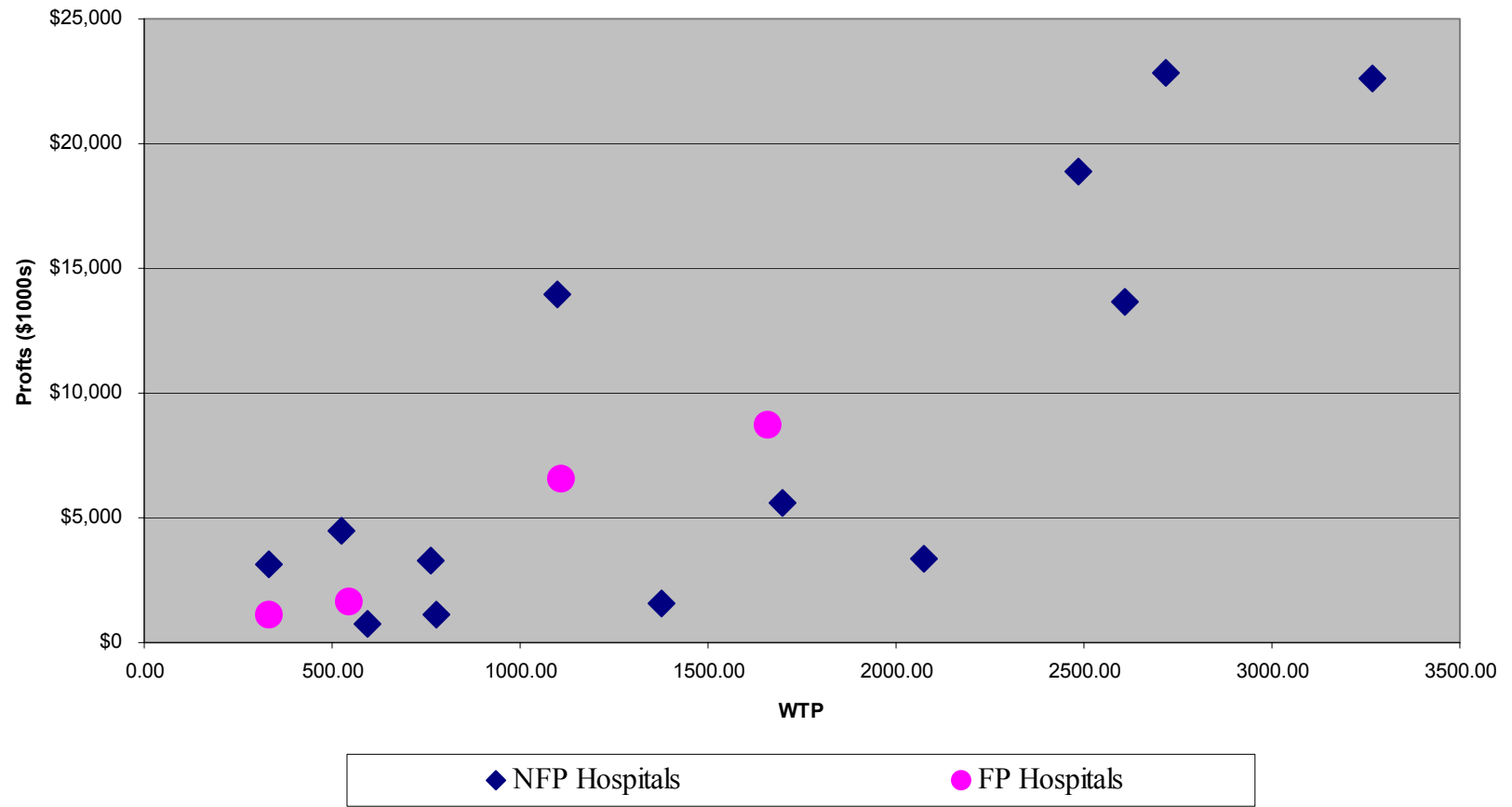


Figure 2: Itemization of WTP by DRG for UCSD and Scripps Chula Vista

