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Competition among hospitals

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We examine competition in the hospital industry, in particular the effect of ownership type (for-profit, not-for-profit, government). We estimate a structural model of demand and pricing in the hospital industry in California, then use the estimates to simulate the effect of a merger. California hospitals in 1995 faced an average price elasticity of demand of −4.85. Not-for-profit hospitals faced less elastic demand and acted as if they have lower marginal costs. Their prices were lower than those of for-profits, but markups were higher. We simulate the effects of the 1997 merger of two hospital chains. In San Luis Obispo County, where the merger creates a near monopoly, prices rise by up to 53%, and the predicted price increase would not be substantially smaller were the chains not-for-profit.

1. Introduction

■ One of the most important sectors of the U.S. economy is health care, accounting for over one trillion dollars in expenditure annually. This sector is also one in which competition is a real issue, given the extensive consolidation that has occurred in recent years (Gaynor and Haas-Wilson, 1999).

During the second half of the 1990s, a dramatic wave of hospital consolidation occurred in the United States. One source puts the total number of hospital mergers from 1994–2000 at over 900 deals (Jaklevic, 2002, and http://www.levinassociates.com), on a base of approximately 6,100 hospitals. Further, many local markets, including quite a few large cities such as Boston, Minneapolis, and San Francisco, have come to be dominated by two or three large hospital systems. Not surprisingly, many health plans have complained about rising prices as a result of this consolidation (Lesser and Ginsburg, 2001).

Hospital markets have been an active area of antitrust enforcement. Since 1984, the federal antitrust authorities have brought 11 suits seeking to block hospital mergers but have won only

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one[1] of the six cases brought since 1993. Not-for-profit status has played a key role in hospital antitrust cases. Not-for-profit hospitals wishing to merge have argued that they will not raise prices after merging because they are motivated by community interest rather than by profit. Court reactions to this have ranged from sympathetic—"The board of University Hospital is quite simply above collusion"[2]—to outright rejection—"no one has shown that [not-for-profit status] makes the enterprise unwilling to cooperate in reducing competition . . . which most enterprises dislike and which nonprofit enterprises may dislike on ideological as well as selfish grounds."[3] On balance, however, the courts have been receptive to this line of argument, particularly in recent years, and the only recent case in which the government has prevailed involved two for-profit hospitals[4] (see Gaynor and Vogt, 2000).

Our goal in this article is to understand the nature of hospital competition and its implications for antitrust policy, in particular, differences in the exercise of market power between for-profit and not-for-profit hospitals. To that end, we estimate a structural model of hospital conduct that explicitly allows for differences between for-profits and not-for-profits, then use the estimates to simulate the effects of a merger. We simulate merger effects both for a merger between for-profits and for a merger between not-for-profits.

Using detailed microdata from California on patients and hospitals in 1995, we find that hospitals face a downward-sloping demand for their products, with an average price elasticity of demand of −4.85. Not-for-profit hospitals face less elastic demand and act as if they have lower marginal costs. Their prices are lower, but markups are higher (26%) than those of for-profits (20%). The merger simulation shows no difference in the tendencies of not-for-profits versus for-profits to exploit merger-created market power. The simulated merger results in postmerger price increases of up to 53%, and changing the firms' profit/nonprofit status has little impact on this figure.

The article is organized as follows. In Section 2 we briefly review relevant prior literature. Section 3 contains a description of the model. The data are discussed in Section 4. Section 5 describes the econometric specification. Section 6 contains the estimates of the structural model. In Section 7 we report a merger simulation highlighting the for-profit/not-for-profit distinction. The conclusion is contained in Section 8.

2. Prior literature

■ To date, the hospital competition literature has consisted largely of structure-conduct-performance (SCP) studies. These studies have found that, at least during the 1990s, hospital prices are lower in less-concentrated markets. There are several reviews of this literature available (Gaynor and Vogt, 2000; Dranove and Satterthwaite, 2000; Dranove and White, 1994). There is more variation, however, in the results of the small number of studies that examine this relationship separately for not-for-profits and for-profits. Three of these studies find that both not-for-profit and for-profit hospitals set higher prices in more-concentrated markets (Dranove and Ludwick, 1999; Keeler, Melnick, and Zwanziger, 1999; Simpson and Shin, 1998). Two others, however, find that not-for-profit hospitals set lower prices in more-concentrated markets, while for-profits set higher prices (Lynk, 1995; Lynk and Neumann, 1999). Although the results from this literature are interesting, SCP methods suffer from well-known deficiencies for testing hypotheses about competitive conduct. In addition, this type of modelling makes it extremely difficult to sort out the differences in results between the studies of not-for-profit pricing. These studies cover different time periods, use different geographic and product markets, and employ different functional forms. The reduced-form framework makes it difficult to assess the reasons for the different results across these studies, let alone evaluate their relative merits.

[1] *FTC* v. *Tenet Healthcare* (1998, US Dist Lexis 11849). Even in this case, however, the government subsequently lost on appeal.

[2] From the District Court's decision in *FTC* v. *University Health*, 1991-1 Trade Cases ¶69,444.

[3] Judge Posner in *HCA* v. *FTC* (1986, 807 F2d 1381).

[4] *FTC* v. *Tenet Healthcare,* (1998, US Dist Lexis 11849). As we mention above, this was reversed on appeal.

There is also an emerging structural hospital competition literature. In this literature, consumer-level data are used to estimate models of demand for hospital services, and then the information from the demand estimation is used to calculate the market power of various hospitals. Town and Vistnes (2001) and Capps, Dranove, and Satterthwaite (2003) each use their demand systems to calculate measures of the marginal value of adding a hospital to a network. Town and Vistnes (2001) then regress prices paid by health plans to hospitals on their measure of a hospital's marginal value and find that hospitals having a high marginal value, either because of isolation in product space or because of high average utility, receive higher payments. Capps, Dranove, and Satterthwaite (2003) regress their marginal-value measure on hospital profit margins and similarly find a positive relationship. Capps et al. (2001), in an approach similar to ours, use their demand estimates to simulate mergers and find that mergers of hospitals even in markets that look quite "competitive" by conventional antitrust methods would nevertheless lead to large price increases.

This article also contributes to the literature on differentiated-product oligopoly by providing evidence from a new market and by using data on individuals. By virtue of the data collected for the hospital industry, we can use microdata on individuals, which has not been commonly utilized in econometric studies of differentiated-product oligopoly (although this has been changing recently). The availability of detailed microdata allows us to flexibly model individual heterogeneity with a directness not possible with aggregate data. The availability of microdata also allows us to employ an instrumenting strategy that differs from those commonly used in the literature.

3. The model

■ We model hospital markets as a differentiated-product oligopoly. Hospitals sell products that are differentiated on a number of dimensions. One of the most important dimensions is physical location. Hospitals have their physical plant in distinct locations, and consumers value proximity to their residences.[5] Hospitals also have different religious affiliations. They are differentiated in the breadth of product lines they offer, in the technological sophistication of their services, in the quality of the "hotel" services they offer, in their use and deployment of staffing, in their mortality rates, and probably in other dimensions as well. It seems reasonable, therefore, to model hospital competition using models of differentiated-product oligopoly.

An added complexity in the case of hospitals is that many hospitals are not-for-profit organizations.[6] A literature has grown up around the idea that not-for-profit hospitals, unlike other firms, do not maximize profits but rather some utility function, possibly reflecting the preferences of the board of trustees, the administrators, the employees more generally, or the physician staff (Newhouse, 1970; Pauly and Redisch, 1973; Lee, 1971; Lakdawalla and Philipson, 1998), and our model reflects the potential for preference differences in the different forms.

Since our goal is a structural, estimable model of demand and supply, we lay out the structure in terms of the demand and supply sides of the model. In what follows we first describe consumers, then producers. On the supply side, we specify a model that explicitly takes into account the differing objectives of not-for-profits and for-profits.

□ **Consumers: basics.** Consumers have a utility function defined over consumption (of non-hospital goods) and the quantity and quality of inpatient hospital care consumed. This utility function depends upon both observable and unobservable (to the econometrician) consumer characteristics and upon both observable and unobservable hospital characteristics.

With some probability consumer i $(= 1, \ldots, I)$ becomes ill. In this case, the indirect utility he derives from consuming q_i units of the inpatient good at hospital j $(= 1, \ldots, J)$ is

$$V_{ij} = -\alpha_i^p p_j q_i + v(q_i, R_i, S_j), \tag{1}$$

[5] This is also true of many other industries. A number of recent articles in industrial organization have focused specifically on the spatial dimension of product differentiation (e.g., Davis, 2001; Manuszak, 1999; Seim, 2001; Pinkse, Slade, and Brett, 2002; Thomadsen, 2002).

[6] 60% of hospitals and 70% of hospital beds were not-for-profit in 1995 (American Hospital Association, 1997).

where p_j is hospital price, R_i are consumer characteristics, and S_j are hospital characteristics. The first term in equation (1) is the indirect utility associated with nonhospital consumption and the second term is the indirect utility from hospital consumption.[7] The consumer chooses the hospital with the greatest V_{ij} and consumes q_i once there.[8]

□ **Hospitals: basics.** Hospitals produce a single output, inpatient hospital care, for which they charge a single price. They face demand $D_j(p)$ (the aggregation over consumers), where p is the vector of all hospitals' prices, and have a cost function $C(\cdot)$. A hospital j, with observable characteristics Z_j and unobservable cost-shifters ζ_j, charging a price p_j, facing other hospitals charging prices p_{-j}, and paying wages W to its inputs, will earn profits of

$$\pi_j = p_j D_j(p) - C(D_j(p); Z_j, \zeta_j, W). \tag{2}$$

A single-hospital, profit-maximizing firm playing a Bertrand pricing game sets its price according to the familiar first-order condition

$$p_j = \frac{\partial C_j}{\partial D_j} - \frac{D_j}{\frac{\partial D_j}{\partial p_j}}. \tag{3}$$

Many hospital firms are not-for-profit, and the theoretical literature typically deals with this by assuming that hospitals maximize a utility function, subject to a break-even constraint. A typical characterization is that not-for-profit hospitals have a mission of providing care to the community. We capture this by specifying the utility function for not-for-profits as depending on quantity produced. We also include profits as an argument to capture any other objectives that not-for-profits may have, thus $U_{NFP} = U(\pi, D)$. Hospitals then choose price to solve

$$\max_{p_j} U_j(\pi_j, D_j) \qquad \text{subject to } \pi_j \geq \pi_{L_j}.$$

In the above, π_{L_j} are the smallest profits (largest losses) a hospital may sustain. Below, μ_j is the Lagrange multiplier on this constraint. The problem leads to a pricing equation (again for a single-hospital firm playing a Bertrand game):

$$p_j = \frac{\partial C_j}{\partial D_j} + \frac{\frac{\partial U_j}{\partial D_j}}{\frac{\partial U_j}{\partial \pi_j} + \mu_j} - \frac{D_j}{\frac{\partial D_j}{\partial p_j}}.$$

This equation suggests that the principal behavioral difference between for-profit and not-for-profit firms is that not-for-profit firms behave like for-profit firms with different cost functions (differing by the utility term—the second term in the expression above). This insight (due to Lakdawalla and Philipson, 1998) is formally correct in our setting with the additional assumptions that (i) the marginal utility of profit is constant and (ii) the profit constraint does not bind. Under those conditions, not-for-profits behave exactly like for-profits, except with different cost functions. Setting the marginal utility of profits to one (without further loss of generality), the previous equation reduces to

$$p_j = \frac{\partial C_j}{\partial D_j} + \frac{\partial U_j}{\partial D_j} - \frac{D_j}{\frac{\partial D_j}{\partial p_j}}.$$

[7] Of course, health insurers play a very large role in consumer choice of hospital, both indirectly by affecting the cost borne by consumers and directly by restricting their choices. We derive the indirect utility function in equation (8) from a model that accounts for the impact of health insurers on consumer choice in an appendix available on the web. See http://www.rje.org/main/sup-mat.html.

[8] We treat q_i as a fixed consumer characteristic. We discuss this assumption and its implications for the econometrics in Section 5.

This property has the benefit that standard techniques now may be applied to the not-for-profit firms. The disadvantage is that (using the pricing equation) we cannot separately identify differences in goals between for-profit and not-for-profit firms from differences in costs between the two forms.[9] Hereafter, we will speak of "behavioral" marginal costs, which we denote $\partial C^B/\partial D$, meaning $\partial C/\partial D$ for for-profit firms and $\partial C/\partial D + \partial U/\partial D$ for not-for-profit firms.

Multiplant firms (called multihospital systems) are common in this industry, so we account for substitution among plants and the coordination of pricing. Let Θ be a $J \times J$ matrix with $\Theta_{jk} = 1$ if hospitals j and k have the same owner and $\Theta_{jk} = 0$ otherwise. Denote by $[\partial D/\partial p]$ the $J \times J$ demand derivative matrix. Stacking up these pricing equations, solving for price, and denoting element-by-element (Hadamard) matrix multiplication by $\circledast$ yields the pricing equation in familiar form:

$$P = \left[\frac{\partial C^B}{\partial D}\right] + \left\{\Theta \circledast \left[\frac{\partial D}{\partial p}\right]\right\}^{-1} D. \tag{6}$$

We have now characterized demand and supply, which form the basis for our econometric model.

4. Data

■ We use data from California's Office of Statewide Health Planning and Development (OSHPD),[10] which maintains a variety of datasets on various aspects of health care in the state. Below we describe each of the particular datasets we draw upon and the criteria for selecting subsets of the data.

□ **Sources.** We draw data for 1995 from three of the datasets maintained by OSHPD: the annual discharge data, the annual financial data, and the quarterly financial data. 1995 is a good year to examine because it falls within the period for which previous studies have found price competition to be present in the hospital sector in California, and it is two years before the date of the merger whose effects we simulate.

Discharge data. Each nonfederal hospital in California is required to submit discharge data to OSHPD. For each patient discharge during the year, a record is generated.

Among the items collected for each discharge are patient demographics (age, sex, race), diagnosis (several DRG and ICD9-CM codes),[11] treatment (several ICD9-CM codes), an identifier for the hospital at which the patient sought care, the patient's zip code of residence, and charges.

Charges are the "list" price for the hospital stay. They are typically presented on a hospital bill as a sum of items multiplied by a list price for each item.[12] The charges that appear on a patient's discharge record are a poor proxy for the transaction price paid to the hospital, especially in recent years. Over time, reimbursement practices have evolved away from insurers more-or-less paying hospital charges. Most insurers negotiate with hospitals over payments that are reductions from charges.[13] As a consequence, charges per se cannot be used as a measure of transaction price; given the way they are calculated, however, they are related to the amount of care a patient consumes.

[9] Not-for-profit and for-profit firms are likely to have different costs because of their different access to capital markets. For-profits can raise capital through equity issue, while not-for-profits cannot. However, not-for-profits can often issue tax-advantaged debt.

[10] http://www.oshpd.cahwnet.gov.

[11] DRG (diagnosis-related groups) and ICD9-CM (*International Classification of Disease*, 9th revision, clinical modifiction) codes are used by all private and public insurers in the United States for recording diagnoses. The ICD9 also includes (separate) codes for treatments.

[12] We do not observe the line-item bill, only the total charges.

[13] At the time of our data, in California a variety of different reimbursement arrangements are seen to be in use among insurers and hospitals. Some insurers pay a negotiated discount off charges. Some pay a negotiated flat per-day cost (called a "per diem"). Some pay an amount per discharge, based upon the diagnosis. Some pay a flat *ex ante* amount per insured, per year—whether or not the insured goes to the hospital.

In addition to the above information, there is a field describing, in general terms, the patient's health insurance information. The field distinguishes among Medicare, Medicaid, Blue Cross, HMO, PPO, other private insurance, self-pay, and a variety of smaller categories.

Financial data. Annual financial disclosures are submitted each fiscal year and whenever a hospital changes ownership. Since these disclosures follow hospital fiscal years, they are not synchronized with calendar years or even with each other.

These reports contain extensive information on each hospital's costs, revenues, capital, physical plant, payroll, outputs, and intermediate production goods, as well as detailed information on ownership and on the type of care the hospital provides (short-term, long-term, psychiatric, etc.). From these data, we will use information on location of the hospital, ownership of the hospital, type of care provided by the hospital, whether the hospital is a teaching hospital or not, and wages. Since we are only using hospital characteristics, which are fixed, and wages, which change slowly over the relevant time period, the lack of synchronization regarding hospital fiscal years is not important for our purposes.

Quarterly financial data. Quarterly financial disclosures are submitted by calendar quarters, so that they are synchronized both with the discharge data and with one another.

For the most part, the quarterly financial data are a subset of the annual data. Information on costs, revenues, and outputs comprise most of the fields. There are, however, a few data elements in the quarterly data that do not appear in the annual data that we use.

"Gross revenues," "net revenues," and "contractual discounts" are broken out in these data by insurance categories. We will use these variables to map from the "charges" for each consumer i in the discharge data to a variable we construct called "net charges," which we will denote $p_j q_i$. The calculation is

$$p_j q_i = charges_i \frac{GRI_j^{oth3^{rd}} + GRO_j^{oth3^{rd}} - DED_j^{oth3^{rd}}}{GRI_j^{oth3^{rd}} + GRO_j^{oth3^{rd}}}. \tag{7}$$

The symbols represent (GRI) gross inpatient revenue from "other third-party" insurers (private third-party insurers, roughly), (GRO) gross outpatient revenues from these insurers, and (DED) contractual deductions from these revenues, i.e., discounts off charges. This variable is obviously measured with error, since discounts off charges probably vary across patients with different insurers, while we have only the total for the hospital as a whole. An additional source of error is the apparently low quality of the financial data: see our discussion in the previous subsection. We sum the quarterly data to annual levels, since the quarterly data are quite volatile.

□ **Selections.** For 1995, there are a total of 3.6 million patient discharges. These break down among insurance plans as in Table 1. For our analysis we will use the discharges whose payment comes from private sources. These are discharges in the HMO, PPO, other private, self-pay, and Blue Cross/Blue Shield categories. These amount to 1.47 million discharges, or about 41% of the total discharges in the state. Our motivation in making these choices is that for patients in these categories, some entity, either the patient or the insurance company, is making explicit choices among hospitals, based, at least in part, on price.[14] In the case of the various insurance categories, insurers have discretion both over which hospitals to include in their networks of approved providers and via any channeling of patients to less expensive hospitals.

More of these observations are lost to some subsequent selections. Only patients seeking care at one of the analysis hospitals (described below) are included. Only patients with a diagnosis (DRG) with a frequency of at least 1,000 are included. Patients with missing values for any of the variables used in any of our analyses or with charges less than 500 or greater than 500,000 are

[14] To some unobserved extent, self-pay patients are "really" charity patients from whom no collection is expected to be possible.

TABLE 1 **Distribution of Discharges by Insurance**

Insurance Type	Frequency	Percentage
Medicare	1,023,160	28.2
Medicaid	960,811	26.5
HMO	780,801	21.5
PPO	336,913	9.3
Other private	145,161	4.0
Self-pay	135,406	3.7
Blue Cross/Blue Shield	74,243	2.0
Various government	86,968	2.4
Various indigent	85,678	2.4

excluded, as are consumers with lengths of stay of zero or greater than 30. After all the exclusions, there are 913,660 remaining observations.[15]

There are 593 total hospitals in the financial data. Of these, 420 are short-term general hospitals (this excludes such institutions as psychiatric hospitals, children's hospitals, rehabilitation hospitals, and other specialty institutions). There are further selections to the hospitals, since some have either missing or useless quarterly financial data (some hospitals had larger deductions from revenue than they had gross revenue, for example).[16] In addition, hospitals associated with staff model HMOs (most notably Kaiser) do not have meaningful prices, since they are vertically integrated with a single insurer; hence, these hospitals are excluded.[17] Finally, we exclude hospitals with fewer than 100 discharges for the year. This leaves us with an analysis sample of 913,660 discharges and 374 hospitals.

□ **Location and constructed variables.** As we describe below, the most important source of identifying variation for our estimation is the relative distance between a consumer and the various hospitals in his choice set. To calculate these distances, we obtained longitude and latitude coordinates from census files for each California zip code appearing in our data. For the hospitals, we obtained each one's longitude and latitude by using the street address available on the financial data and the website http://www.MapsOnUs.com, run by Etak, a geographical information systems firm. Great circle distances are then easily calculated from each zip code's coordinates to each hospital.

In addition, we constructed several variables that we use in our analysis. The technology index is the sum over dummy variables for the presence of some 28 technologies reported in the annual financial data (e.g., the presence of an MRI, open heart surgical suite, etc.). The wage index is a Paasche wage index calculated relative to the average hospital over 10 job classifications (e.g., registered nurse, orderly, etc.). The dummy for teaching status takes on a value of one for hospitals with a program to train resident physicians.

Table 2 contains variable descriptions and descriptive statistics.

5. Econometric specification and estimation

■ We proceed in several subsections. On the demand side, we impose a functional form and discuss the separation of price and quantity made necessary by the limitations of our data and then

[15] As can be observed from Table 1, most of the reduction (1.5 million discharges) in the analysis sample comes from eliminating discharges with a public insurer (Medicare, Medicaid); another 600,000 discharges are eliminated due to being treated at a specialty hospital as opposed to a short-term general hospital.

[16] Hospitals with strange data for these variables are disproportionately small hospitals, so many are eliminated by a later criterion anyway.

[17] Notice that this means that we are ignoring a possible avenue of substitution: from our sample of hospitals to Kaiser hospitals via a change in insurer.

TABLE 2 Variable Descriptions

Name	Description	Mean	Standard Deviation
X	**Consumer Characteristics**		
q	E(quantity) from equation (9)	1.24	1.61
HMO	Membership in HMO	.50	
PPO	Membership in PPO	.31	
Unscheduled	Unscheduled admission	.53	
d	**Distance**		
$d_{i\to j}$	Distance to (chosen) hospital (miles)	11.56	27.78
$d_{i\to j}^2$	Distance^2		
Z	**Hospital Characteristics**		
p	E(price) from equation (9)	4696	1603
FP	For-profit status	.28	
NFP	Not-for-profit status	.52	
Teach	Teaching hospital	.21	
Tech Index	Technology index	15.02	6.06
System	Multihospital system member	.49	
W	**Input Prices**		
W	Wage index	.99	.15

discuss our identification strategy. Then, we review a standard model of the supply side, making such modifications as are necessary to address the for-profit/not-for-profit question.

□ **Demand.** Our demand system is generated by a discrete continuous-choice problem (Dubin and McFadden, 1984) in which each consumer first makes a discrete choice (which hospital to visit), followed by a continuous choice (how much care to receive at his chosen hospital). Thus, each consumer's demand response to a price change by a hospital has three components: first, the consumer may choose not to consume hospital care at all; second, the consumer may switch from one hospital to another; and third, the consumer may reduce the quantity consumed once he arrives at the chosen hospital.

Throughout our analysis, we assume that the first and third responses have a price elasticity of zero. That is, we assume that there is no outside good and that the quantity of care consumed by consumer i is a fixed characteristic of that consumer, q_i. These assumptions are reasonable, based on the results of the RAND Health Insurance Experiment. The findings of that experiment include a very low price elasticity of demand for hospital care and a finding that virtually all of the reduction in the consumption in health care arising from a price increase occurred as a result of a reduction in the probability of obtaining care: virtually none of it resulted from a reduction in the quantity of care used conditional on having obtained it (Manning et al., 1987; Newhouse, 1993; Keeler et al., 1988).

These assumptions simplify our analysis considerably. First, assuming no outside good obviates the need to deal with our lack of information on most of the consumer characteristics for people choosing the outside good—unlike previous applications, we do not know even the distribution of many characteristics for consumers who do not consume care. Second, assuming fixed q_i ameliorates the central data problem: that we do not observe either price or quantity, only a measure of expenditure. As we have discussed elsewhere (Gaynor and Vogt, 2003), this makes identification impossible absent an assumption like the one we make here.[18] Assuming fixed q_i makes it relatively easy to separate price from quantity, as we discuss below.

[18] We thank an anonymous referee for pointing out that, using the functional form in our above-cited working paper, it is impossible to deal coherently with inelastic demand. Nevertheless, our discussion there does establish the identification difficulty.

Finally, we will also assume that although q_i has a stochastic element, ν_i, this element is unobserved by consumers and firms prior to the consumers' hospitalizations. Again, we think this assumption is reasonable, given, first, that most hospitalizations contain both diagnostic and treatment components, so that agents are clearly at least somewhat uninformed about the quantity of care needed, and, second, that our exogenous consumer characteristics are quite detailed concerning which diagnoses and procedures were associated with the hospitalization—indeed, one could plausibly argue that the econometrician knows more here than do the market participants at the time the hospitalization decision was being made.

Functional form. We now convert equation (1) into a form suitable for estimation. There are L observable consumer characteristics, $X_{i\ell}$, and K observable hospital characteristics, Z_{jk}. $d_{i\to j}$ is the distance between a consumer's residence and the hospital, and hospital price is p_j. Unobservable producer characteristics consist of an unobserved quality, ξ_j. Consumer i's unobserved, idiosyncratic taste for hospital j is ε_{ij}. We use the following functional form for V_{ij}:

$$V_{ij} = -\tilde{\alpha}_i^p p_j E\{q_i\} + +\tilde{\alpha}_i^d d_{i\to j} + \tilde{\alpha}_i^{d^2} d_{i\to j}^2 + \sum_{k=1}^{K} Z_{jk}\tilde{\alpha_{ik}} + \xi_j + \varepsilon_{ij}, \tag{8}$$

where

$$\begin{aligned}
q_i &= \exp\left(\sum_{\ell=1}^{L} X_{i\ell}\beta_\ell + \nu_i\right)\\
\tilde{\alpha}_i^p &= \exp\left(\alpha_0^p + \sum_{\ell=1}^{L} X_{i\ell}\alpha_\ell^p\right)\\
\tilde{\alpha}_i^d &= \rho + \sum_{\ell=1}^{L} X_{i\ell}\rho_\ell^X\\
\tilde{\alpha}_i^{d^2} &= \rho^2 + \sum_{\ell=1}^{L} X_{i\ell}\rho_\ell^{2X}\\
\tilde{\alpha}_{ik} &= \alpha_0 + \sum_{\ell=1}^{L} X_{i\ell}\alpha_{lk} + \rho_k^Z d_{i\to j} + \rho_k^{2Z} d_{i\to j}^2.
\end{aligned}$$

Notice that, as stated in the previous subsection, the stochastic part of quantity (ν_i) is unobserved by the consumer when choosing among hospitals: $E\{q_i\}$ enters utility, not q_i. Here ε_{ij} is an i.i.d. Weibull random variable. In much of the previous literature, the equivalents of our α and β coefficients have been modelled using random-coefficients methods. Absent individual heterogeneity, popular discrete consumer-choice models have the undesirable property of a fixed relationship between market shares and own- and cross-price elasticities of demand.[19] With aggregate data, individual heterogeneity can be introduced via random coefficients.

However, the observability of consumer-level characteristics, especially distance, obviates much of the rationale for including these effects. The nature of our data, with detailed information on individuals, allows us to account explicitly for observable individual heterogeneity. Distance in particular has been shown to be one of the most important determinants of hospital choice.[20] In our model hospitals physically close to one another have much higher cross-price elasticities than do hospitals far apart, breaking the inflexible relationship between market share and elasticity.

Separating p and q. Given our assumption of zero demand elasticity, once a consumer has arrived

[19] This is certainly true of the logit model, which we use, but is due to the assumption that unobservable consumer tastes are distributed i.i.d., not any assumption about the specific form of their distribution.

[20] This is true both in the more recent structural literature and in an older hospital-demand literature (see a partial review in Gaynor and Vogt, 2000).

at a hospital, separating price and quantity is straightforward, using the accounting identity:

$$\ln p_j q_i = \ln p_j + ln q_i = \sum_j \chi_{i\to j} \ln p_j + \sum_\ell X_{i\ell}\beta_\ell + \nu_i. \tag{9}$$

Here, $\chi_{i\to j}$ is a dummy variable taking on the value one when consumer i goes to hospital j. Once this equation is estimated, we may fix X_i at some value (we take means over the entire sample) and define $E(q_i) = 1$ for that X_i. Then, equation (9) can be used to predict expected expenditures for this "standard" discharge, giving a measure of p for each hospital.[21]

Estimating equations. To generate estimating equations for demand, we follow Berry, Levinsohn, and Pakes (1998), who discuss the estimation of models in this class using microdata. It is tempting to estimate equation (8) using a logit maximum-likelihood routine. However, under virtually any oligopoly model of price setting, p_j will be correlated with ξ_j, part of the error. So, simultaneous-equations bias will render the estimates inconsistent.

We now rewrite and slightly generalize equation (8). We absorb the hospital's price into Z_j and $E\{q_i\}$ into X_i, incorporate all of the interaction terms in X and α, and express the equation as a "mean" level of utility of hospital j, δ_j, and deviations from the mean. This gives us the following two equations:

$$\begin{aligned} EV_{ij}^* = \delta_j &+ \sum_{k=1}^{K}\sum_{\ell=1}^{L}\alpha_{lk}(X_{i\ell} - \overline{X}_{i\ell})Z_{jk} \\ &+ \rho d_{i\to j} + \sum_{\ell=1}^{L}\rho_\ell^X X_{i\ell} d_{i\to j} + \sum_{k=1}^{K}\rho_k^Z Z_{jk} d_{i\to j} \\ &+ \rho^2 d_{i\to j}^2 + \sum_{\ell=1}^{L}\rho_\ell^{2X} X_{i\ell} d_{i\to j}^2 + \sum_{k=1}^{K}\rho_k^{2Z} Z_{jk} d_{i\to j}^2 + \varepsilon_{ij} \end{aligned} \tag{10}$$

and

$$\delta_j = \sum_{k=0}^{K} Z_{jk}\overline{\alpha}_k + \xi_j. \tag{11}$$

We can now estimate (10) by logit maximum likelihood, including a dummy variable for each hospital and covariates for all interactions among the consumer and hospital characteristics. Then, after the δ_j have been estimated, they can be used as left-hand-side variables in (11) to obtain estimates of $\overline{\alpha}_k$. This second-stage regression will involve instrumenting for p_j, since the same endogeneity that makes maximum likelihood on (8) undesirable would also militate against using ordinary least squares (OLS) on (11).

Instruments. Good instruments for the demand equation are factors that affect the firm's pricing but are uncorrelated with unobserved quality. The obvious places to look are factors that affect marginal cost or demand. Cost shifters, such as wages, meet this criterion. In addition, we have information on product and consumer characteristics, which affect demand and, hence, the degree and closeness of competition a firm is facing.

Like much of the previous literature (e.g., Bresnahan, 1981, 1987; Berry, Levinsohn, and Pakes, 1995),[22] we assume that the firm-specific shock (ξ_j) is mean independent of product characteristics and cost shifters. Unlike much previous work, however, we have microdata on

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[21] If, contrary to our claim, patients have more information (about ν_i) than does the econometrician, sicker (healthier) patients may choose lower (higher) priced hospitals; thus, the distribution of prices generated by our method may be compressed relative to the true distribution.

[22] See Nevo (1998) for a clear exposition of instrumenting strategies.

consumer characteristics. We assume unobserved quality is also independent of consumer characteristics. Thus, in addition to product characteristics, we also employ interactions of consumer and producer characteristics as instruments, in particular the distances between every consumer and every hospital. As in other applications, since there are many characteristics, we have to reduce the dimensionality of the instrumental variables via functions of these characteristics. Berry, Levinsohn, and Pakes (1995) (and much of the literature) use own-product characteristics and sums of other product characteristics. Since we have microdata on consumer characteristics, we can pursue another approach. We use the demand function to capture directly the effects of characteristics.

Consider the supply side of the market, in the form of the pricing equation (for a single-hospital firm):

$$p_j = \frac{\partial C^B}{\partial D}(D_j, W_j, Z_j, \zeta_j) - \frac{D_j}{\frac{\partial D_j}{\partial p_j}}. \tag{12}$$

Obviously, factors that affect marginal cost or the markup and are independent of unobserved quality are suitable instruments. Of the variables in this equation, D_j, W_j, and $\partial D_j/\partial p_j$ do not appear on the demand side. However, D_j and $\partial D_j/\partial p_j$ are themselves endogenous, as both depend upon price. So, as instruments for the demand side, we have W_j and any exogenous variables that shift D_j and $\partial D_j/\partial p_j$. Now we know that, in expectation,

$$\widehat{D_j} = \sum_{i=1}^{I} Pr\{i \to j \mid p, \xi\} E(q_i) \tag{13}$$

$$\widehat{\frac{\partial D_j}{\partial p_j}} = \sum_{i=1}^{I} \frac{\partial Pr\{i \to j \mid p, \xi\}}{\partial p_j} E(q_i). \tag{14}$$

$\Pr\{i \to j \mid p, \xi\}$ depends upon p_j and on ξ_j, so it is endogenous. However, it also depends upon the distances between consumer i and all of the hospitals. As we say above, these distances are presumed exogenous. In addition, $\Pr\{i \to j \mid p, \xi\}$ depends upon the interactions among exogenous consumer and producer characteristics. These observations suggest an instrumenting strategy. We can calculate an instrumental variable, D_j^{IV}, by evaluating (13) at $\xi = 0$ and omitting all terms involving price, so that D_j^{IV} depends only upon exogenous distances and interactions between consumer and producer characteristics. In a similar manner, an instrument for $D_j/(\partial D_j/\partial p_j)$ can be calculated. This latter instrument is similar to Berry, Levinsohn, and Pakes (1998), who use predictions of the markup as an instrument.

Note that in order to calculate the instruments, we need parameter estimates from equation (11). However, as we said, we need to estimate this equation via instrumental variables. We therefore employ the following strategy to generate the instrumental variables. We calculate $\Pr\{i \to j\}$ using the parameter estimates from the multinomial logit hospital choice equation (10), where the estimates of δ_j and the coefficients on all terms involving price are set equal to zero. This probability is thus purged of any influence of price and depends only on exogenous variables, notably distance. We calculate $E(q_i)$ using parameter estimates from the regression for separating price and quantity, equation (9), i.e., $E(q_i) = \sum_\ell X_{i\ell}\hat{\beta}_\ell$. We then calculate the instruments as defined in equations (13) and (14). The average utility equation (11) is now estimated, using these to instrument for price. This gives us first round estimates of the average utility parameters ($\overline{\alpha}$). We can then calculate values of δ_j, setting ξ_j and price terms equal to zero. This yields estimates of the probability that consumer i goes to hospital j (see equation (10)) and its derivative with respect to price, which are then used to construct the final instruments.

The approach we describe here is similar to instrumenting strategies commonly employed in much of the empirical work on differentiated-product oligopoly, in that it also employs functions of presumed exogenous product characteristics and cost shifters as instruments. We differ from the more standard approach by relying on the form of demand to summarize the effects of the characteristics.

We should also be clear that the more common approaches to instrumenting in empirical work on differentiated-product oligopoly are not feasible for our application. Berry, Levinsohn, and Pakes (1995) use own-product characteristics, the sum of characteristics of other products produced by the same firm, and the sum of characteristics of products produced by other firms as instruments. The variation in their instruments comes from time-series variation, variation in the set of other products, and variation in the products produced by other firms. We have no time-series variation, since we use a single cross-section. Most of our sample consists of single-hospital firms, and these hospitals have no characteristics of other products sold by the same firm. In addition, for single-hospital firms, the variation in characteristics of products produced by other firms is perfectly correlated with own characteristics.

Another approach to instrumenting has been to use prices of the same product in other geographic locations (Hausman, 1996; Nevo, 2000). This method relies on predefined geographic markets and on firms operating in multiple geographic markets. Since we do not presuppose geographic market boundaries, and since most of the hospitals in our data operate in a single geographic location, this approach is not feasible for our application.[23]

□ **Supply.** We turn to deriving an estimating equation for the supply side. The supply side is simply the pricing equation (6). Rearranging and employing a linear functional form for marginal costs yields

$$P - \left\{\Theta \circledast \left[\frac{\partial D}{\partial p}\right]\right\}^{-1} D = \omega_0 + D\omega_D + W\omega_W + Z\omega_Z + \zeta. \qquad (15)$$

The second term on the left-hand side (the markup) is calculated after estimating the demand side. On the right-hand side, D is endogenous, but the other variables are assumed exogenous. Again, D_j^{IV} is an instrument, as it depends only upon presumed exogenous location and interactions between producer and consumer characteristics.

□ **Estimation procedure.** The estimation proceeds in four steps. First, the expenditure equation (9) is estimated via OLS. From this, p and q are backed out and used in the next step, which is the estimation of the multinomial logit demand system (10) by maximum likelihood. The δ recovered from this estimation are then used as left-hand-side variables in the estimation of the average effects of p and Z on demand in (11), estimated by two-stage least squares (2SLS). Finally, the parameters from the demand estimation are used to calculate the left-hand side of the pricing equation (15), and it is estimated via 2SLS.

6. Results

■ There are four estimations to discuss: the separation of price and quantity, the large discrete-choice demand estimation that produces δ, the estimation of the determinants of δ, and the pricing equation.

□ **Prices and quantities.** Equation (9) is estimated on the set of 913,660 discharges from the 374 analysis hospitals. The regression is run with log net expenditure as the left-hand-side variable. Right-hand-side variables are the 374 hospital dummies, 13 dummy variables for age categories, 1 dummy variable for sex, 5 dummy variables for race categories, 305 variables for DRG dummies, 3 dummy variables for "severity," 3 dummy variables for type of admission (scheduled, unscheduled, newborn, unknown), 24 dummy variables for the number of other diagnoses (the number of other illnesses the consumer has in addition to the one for which he was admitted), and interactions

[23] One of the strengths of our approach is that it lets the data tell us through the demand function which hospitals in which locations are competitors, i.e., what the geographic market is.

between 23 variables for major diagnostic category (a more granular measure of diagnosis) and the age, sex, race, severity, type of admission, and other diagnosis dummies. There are 1,792 right-hand-side variables in total. The R^2 for the equation is .81.

We can now calculate price and quantity as described previously using the estimates from this regression. The average hospital price is \$4,696 (standard deviation \$1,603). Government hospitals have the highest prices (recall, on private-pay patients), at \$4,957 (standard deviation \$1,826) per adjusted discharge. For-profit hospitals have higher prices, \$4,793 (standard deviation \$1,554), than do not-for-profit hospitals at \$4,545 (standard deviation \$1,527). Quantity per consumer is highest at not-for-profits at 1.24 (standard deviation .36). Quantity is 1.20 (standard deviation .38) at for-profits, and 1.11 (standard deviation .26) at government hospitals.[24]

□ **Demand logit.** The demand logit contains a full set of hospital dummies (373 dummy variables for the 374 hospitals). In addition, it contains a full set of interactions among the five hospital characteristics and the four consumer characteristics. These variables have been previously described in Table 2. There are 20 interactions between hospital and consumer characteristics. In addition, we include distance, distance squared, and interactions between these and both consumer and hospital characteristics, for an additional 20 parameters.

The multinomial logit estimation includes 913,660 observations, 374 choices, and 413 parameters. The results of this estimation appear in Table 3 (omitting the coefficients on the 373 hospital dummies).

The results in Table 3 are, for the most part, intuitive. Consumers who will consume more care are more price sensitive. HMO and PPO consumers are more price sensitive, the increase in the price coefficient being about 13% and 10% respectively. Higher-demanding consumers (perhaps "sicker") value teaching hospitals and high-tech hospitals more. People whose admissions are unscheduled are less price sensitive and more distance sensitive. In addition, as indicated by the means of the hospital dummies (δ_j) by ownership class, for-profit and not-for-profit hospitals are more attractive to consumers than government hospitals ($\overline{\delta}_{NFP} = 1.65$, standard deviation 3.03; $\overline{\delta}_{FP} = 1.83$, standard deviation 1.83; $\overline{\delta}_{govt} = -1.18$, standard deviation 3.01).

□ **Average utility.** Now we turn to the estimation of the mean utility levels. Recall that we are estimating (11), the demand equation. The endogenous variable in the demand equation is price. Ownership, teaching, technology, and wages are exogenous. We use the exogenous location of consumers and hospitals to derive our key instruments, D_j^{IV} and $D_j/(\partial D_j/\partial p_j)^{IV}$. Both variables are correlated with variables in the firm's pricing equation, the first because of scale economies and the second because of market power. The wage index provides an additional instrument, and the nonprice characteristics of hospitals are presumed exogenous throughout. The results appear in Table 4. We report both OLS and 2SLS estimates.

OLS produces an estimate of the coefficient on price of the "right" sign. As we add instruments, however, the price coefficient becomes more negative. The coefficient of -1.22 on price (in thousands of dollars) corresponds to an average demand elasticity facing hospitals of -4.85 (standard deviation 2.03). The elasticity for for-profit firms is -5.52 (standard deviation 2.07), and for government hospitals it is -4.68 (standard deviation 2.43). Not-for-profit hospitals on average face an elasticity of -4.55 (standard deviation 1.74).[25] As indicated by the estimates for the relevant dummy variables, on average, consumers prefer for-profit to not-for-profit to government hospitals; they also prefer teaching and high-tech hospitals.

The instruments for this regression performed quite well. The simple correlation between price and $D_j/(\partial D_j/\partial p_j)^{IV}$ is .11 ($P < .03$),[26] and the simple correlation between price and

[24] These figures are means over hospital means; thus, they are not inconsistent with the overall mean reported in Table 2.

[25] Note that there are not separate estimates of price coefficients by ownership type. The differences in elasticities derive from differences in the geographic distribution of consumers and hospitals by ownership type.

[26] P here denotes p-value.

TABLE 3 Multinomial Logit Results

Variable	Estimate	Standard Error
$p\ q$	−.0261	.0005
p HMO	−.157	.002
p PPO	−.121	.003
p Unscheduled	.006	.002
FP q	.082	.004
FP HMO	.721	.016
FP PPO	.787	.018
FP Unscheduled	−.195	.013
NFP q	.046	.003
NFP HMO	.617	.013
NFP PPO	.695	.015
NFP Unscheduled	−.216	.011
Teach q	.040	.002
Teach HMO	.285	.008
Teach PPO	.078	.009
Teach Unscheduled	.052	.006
Tech Index q	.009	.0002
Tech Index HMO	.048	.001
Tech Index PPO	.034	.001
Tech Index Unscheduled	−.028	.001
$d_{i \to j}$	−23.92	.05
$d_{i \to j}^2$	3.15	.01
$d_{i \to j}\ q$	.717	.003
$d_{i \to j}^2\ q$	−.119	.001
$d_{i \to j}$ HMO	−6.517	.018
$d_{i \to j}^2$ HMO	1.023	.003
$d_{i \to j}$ PPO	−2.860	.017
$d_{i \to j}^2$ PPO	.412	.003
$d_{i \to j}$ Unscheduled	−1.909	.014
$d_{i \to j}^2$ Unscheduled	.314	.003
$d_{i \to j}\ p$	.596	.005
$d_{i \to j}^2\ p$	−.069	.002
$d_{i \to j}$ FP	.621	.035
$d_{i \to j}^2$ FP	−.080	.008
$d_{i \to j}$ NFP	.280	.029
$d_{i \to j}^2$ NFP	−.022	.007
$d_{i \to j}$ Teach	4.06	.019
$d_{i \to j}^2$ Teach	−.583	.005
$d_{i \to j}$ Tech Index	.048	.002
$d_{i \to j}^2$ Tech Index	−.004	.001

the wage index is .15 ($P < .01$). In the first-stage regression (reported in the Appendix), both W and $D_j/(\partial D_j/\partial p_j)^{IV}$ are individually highly significant, with the "right" signs, while D^{IV} is insignificant. The F-statistic for the first-stage regression is 4.91, yielding significance at better than the 1% level, and the F-statistic for the joint exclusion of the three price instruments is 6.54 ($P < .01$).

□ **Supply.** The estimates of the pricing equation (15) appear in Table 5. The table contains both OLS and 2SLS estimates. The instruments for this regression are the nonprice hospital characteristics, D^{IV}, and squares and interactions of these. Both the left-hand-side variable and quantity, a right-hand-side variable, are measured in thousands. In what follows, we discuss the 2SLS estimates.

TABLE 4 **Demand Equation**

Variable	OLS	2SLS
Constant	−1.92 (.53)	1.40 (1.84)
p	−.52 (.08)	−1.22 (.38)
FP	3.16 (.36)	3.15 (.40)
NFP	1.54 (.34)	1.27 (.40)
Teach	.22 (.32)	.67 (.43)
Tech Index	.25 (.02)	.25 (.03)
R^2	.42	
N	374	374

Standard errors in parentheses.

TABLE 5 **Pricing Equation**

Variable	OLS	2SLS
Constant	.008 (.64)	.43 (.70)
W	3.24 (.65)	2.82 (.70)
D	−.15 (.11)	.16 (.20)
$D\times$ FP	−.10 (.14)	−.30 (.25)
$D\times$ NFP	.07 (.11)	−.17 (.19)
FP	.91 (.31)	1.07 (.43)
NFP	−.12 (.29)	.10 (.37)
Teach	.87 (.23)	.90 (.24)
Tech Index	.03 (.02)	.002 (.25)
System	−.52 (.18)	−.48 (.19)
R^2	.17	
N	374	374

Standard errors in parentheses.

Recall, we are recovering estimates of the parameters of behavioral marginal cost. The point estimates here indicate decreasing returns to scale for the government hospitals and increasing returns to scale for for-profit and not-for-profit hospitals. The effect sizes are modest, however, and the scale economies are neither singly nor jointly significant at conventional levels.

We previously noted that for-profits price on average $248 (standard error $187) higher than do not-for-profits. This difference is accounted for by differences in behavioral marginal costs and differences in markups. Table 5 reveals that the behavioral marginal cost intercept for for-profits is about $966 (standard error $421) higher than it is for not-for-profits (recall that the left-hand-side variable is measured in thousands). This difference diminishes with expanding output, and at 7,829 (standard error 9,821) adjusted discharges and above, the not-for-profits' behavioral marginal costs are higher. Eight thousand discharges is a large hospital but is within the range of the data. At sample means, for-profits have behavioral marginal costs about $592 (standard error $329) higher than do not-for-profits. Average markups are $1,183 (standard deviation $587) for not-for-profits and $948 (standard deviation $345) for for-profits. These represent a 26% markup on average for not-for-profits and a 20% markup for for-profits.

The teaching and technology variables are of the "right" sign, and the teaching dummy's coefficient is significant. The system variable indicates that members of multihospital systems enjoy marginal costs about $480 lower than nonmembers.

Instrument performance is again good.[27] The simple correlation between D and D^{IV} is .53 ($P < .01$), and the correlations between $D \times FP$ and $D^{IV} \times FP$ and $D \times NFP$ and $D^{IV} \times NFP$

[27] Since the regressions are long, we don't report the entire set of estimates here.

are .66 and .75, both ($P < .01$). The three first-stage regressions each have F-statistics significant at better than 1% overall, and the exclusion restrictions for the instruments not in the second-stage equations are rejected in all three equations at (much) better than the 1% level.

In terms of behavioral differences, the results indicate both lower pricing and lesser apparent scale diseconomies for not-for-profits compared to for-profits. As we indicated previously, we cannot separate these differences into cost and utility differences. In our model, behavioral differences with respect to merger analysis arise through behavioral scale economies: as a general rule, hospitals with greater scale economies will raise their prices more as a result of a merger. Since, at point estimates, not-for-profit hospitals do have lesser scale economies, our results are in the direction for not-for-profits to raise their prices less in response to merger. We assess the size of this effect in the merger simulation in the next section.

□ **Elasticities and specification.** A common criticism of linear random-utility demand specifications is that the use of such models at the aggregate level leads to own- and cross-price elasticities that depend only upon the price parameter, market shares, and prices. The common response to this in the literature to date has been to use a random-coefficients model in order to introduce the possibility of richer substitution patterns.

We argue that the use of rich microdata with a conventional, fixed-coefficient linear random-utility model can be a good substitute for the more technique-intensive random-coefficients models. In particular, interaction effects among consumer and product characteristics serve the same role as the random coefficients in prior work, and, in fact, those random coefficients are sensibly interpreted as summarizing the effects of consumer characteristics necessarily omitted in market-level demand estimation. In our application, geographical distance between the consumer's residence and the hospital (in effect an interaction of the consumer's location with the hospital's location) produces a rich substitution pattern, at least along this observable dimension. We turn now to an empirical defense of this argument.

Consider the elasticities generated by a conventional, fixed-coefficient, market-level logit model. A product's own-price elasticity of demand is given by $e_{jj} = \alpha_p(1 - s_j)p_j$, where α is the slope on price and s_j is the product's market share. So, just as a mechanical matter, if we were to regress the log absolute value of own-price elasticity on the log of one minus market share and log own price, then in the logit model we would achieve an R^2 of unity.

Similarly, the elasticity of the demand for product j with respect to the price of product j' is $e_{jj'} = -\alpha_p s_{j'} p_{j'}$ Again as a mechanical matter, a regression of $\log(e_{jj'})$ on log market share and log price for product j' would yield an R^2 of unity. To examine how much our estimated demand system deviates from a simple, aggregate logit, we present some scatterplots and run the regressions suggested above.

Figure 1 is a scatterplot of cross-price elasticities calculated from our estimated demand system against distance. Each point in the plot is a cross-price elasticity. The y-axis is cross-price

FIGURE 1

SPATIAL DIFFERENTIATION

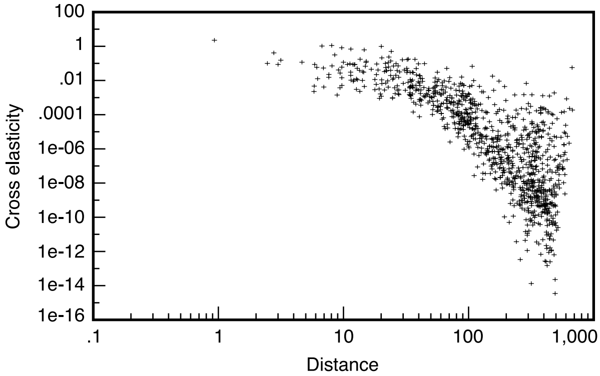
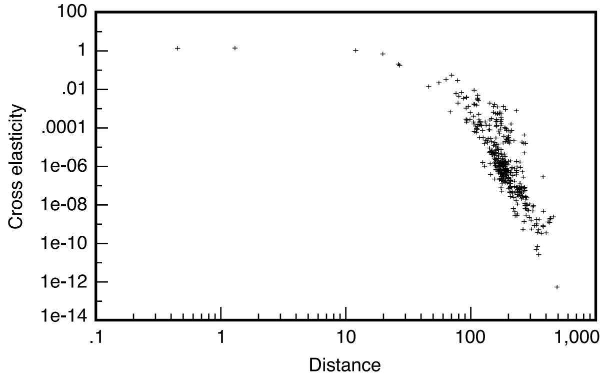


FIGURE 2

SUBSTITUTION WITH FRENCH HOSPITAL



elasticity on a log scale but labelled in levels. The x-axis is distance on a log scale but labelled in levels. For legibility, the plot presents 1,000 randomly selected cross-price elasticities out of the total of 139,502 (two for each of the 69,751 hospital pairs). As is readily apparent, distance has a strong effect on cross-price elasticity: hospital pairs that are closer together have higher cross-price elasticities. The simple correlation, in the universe of 139,502, between log cross-price elasticity and log distance is $-.78$.

In Figure 1 we are not "controlling" for either the price or market share of the j' hospital. To do this, we construct Figure 2. This figure contains the elasticity of demand for each of the other 373 hospitals with respect to the price of French Hospital in San Luis Obispo (this hospital is important to our merger simulation in the next section). If our model were to be roughly comparable to a simple logit, these elasticities should all be the same—they should depend only on the price and market share of French Hospital. As is again apparent, the elasticities are different and bear a strong relationship to distance from French Hospital. The simple correlation between log elasticity and log distance is $-.73$ here.

Turning to the regression models suggested above, when we regress log absolute own-price elasticity against log own-price and log one minus own market share, the R^2 is .38, substantially less than unity. Adding the log distance to the nearest hospital increases R^2 to .54, and a 1% rise in nearest-neighbor distance decreases own-price elasticity by .14%. Similarly, when we regress log cross-price elasticity on log market share and log price, we obtain an R^2 of .13, far from unity. Including the log of distance between the hospital pairs increases this figure to .71, and the effect of a 1% rise in distance is to reduce cross-price elasticity by 4.5%.

We conclude from this analysis that our estimated model differs substantially from a market-level logit model and that, along the important dimension of geographical location at least, it captures a much richer substitution pattern than would a fixed-coefficient market-level logit.

7. Merger simulation

■ To assess the implications for merger analysis of differences between for-profit and not-for-profit hospitals, we simulate a 1997 merger using our estimated model. There is now a substantial literature on merger simulation in antitrust contexts (see, for example, the special issues introduced by Froeb and Werden, 2000; Muris, 1997). Most commonly, the demand systems used in estimation and simulation are aggregate in nature, the aggregate logit system (Werden, Froeb, and Tardiff, 1996) and the AIDS system (Hausman, Leonard, and Zona, 1994) being examples. For a discussion of the effect of functional form on merger simulation, see Crooke et al. (1999) and Peters (2002).[28] For a nonsimulation evaluation of a consummated hospital merger, see Vita and Sacher (2001).

[28] Peters (2002) also evaluates the performance of various methods of merger simulation.

TABLE 6 **San Luis Obispo County Hospitals**

Hospital	Owner	p	D	Beds	Distance (Miles)
French Hospital	Ornda	4,434	2,179	147	.28
General	County	4,577	255	46	.72
Sierra Vista	Tenet	4,134	3,722	186	.99
Arroyo Grande	Vista	3,477	546	65	12.03
Twin Cities	Tenet	4,216	1,683	84	19.21
Marian Medical Center	Catholic	3,289	2,240	225	26.24
Valley Community	Ornda	4,439	2,313	53	26.79

Standard errors in parentheses.

In 1997, Tenet Healthcare Corp and Ornda Healthcorp, two for-profit hospital corporations, merged. Both were national hospital corporations, and both had a substantial presence in California. Of our 374 analysis hospitals in 1995, Ornda owned 21 and Tenet owned 14.

There was overlap in the service areas of the Tenet and Ornda hospitals. Tenet operated nine and Ornda seven hospitals in Los Angeles County; each operated one in San Diego county; and Ornda operated one and Tenet operated two in San Luis Obispo County. There were, however, 101 and 23 hospitals respectively in Los Angeles and San Diego Counties, whereas there were only five in San Luis Obispo County, of which Tenet and Ornda together owned the three largest. The Federal Trade Commission (FTC) permitted the merger to go through, but it required in a consent order that the merged entity divest one hospital, French Hospital Medical Center, in San Luis Obispo. This hospital was subsequently divested to Vista Hospital Systems, which also owned Arroyo Grande Hospital in the county.

In our merger simulation, we analyze the Tenet/Ornda merger under three different scenarios. First, we simulate the merger assuming no divestiture of French Hospital. Second, we simulate the merger assuming divestiture of French Hospital. Third, we simulate the merger without divestiture under the counterfactual assumption that Tenet and Ornda were not-for-profit. The idea of the third simulation is to test the theory that not-for-profit hospitals behave differently after gaining market power through a merger. In all three mergers, we track the prices in San Luis Obispo, Los Angeles, and San Diego counties.

It turns out that San Luis Obispo County is the most interesting, so we provide a description of the hospitals there. There are five hospitals in San Luis Obispo County and two more within fifty miles of San Luis Obispo. The hospitals are described in Table 6. The first three hospitals are "in town" in San Luis Obispo, the next two are in San Luis Obispo County, and the remaining two are outside San Luis Obispo County but within fifty miles. The distance measure is the distance between the hospitals and the unweighted centroid of the first three hospitals in the table.

Table 7 contains the price elasticities for these hospitals. Own-price elasticities are on the diagonal. The off-diagonal elements are read as the elasticity of the row hospital's demand with respect to the column hospital's price. Thus, a 1% price increase at French Hospital would cause a 1.47% demand increase at Sierra Vista. In the table we can see the similarities and differences between our model and the simple logit. Were our demand system identical to the simple logit, the (nondiagonal) elements of each column would be identical. For the three hospitals that are in town, these columns are nearly consistent with the logit model: these hospitals are all less than 1.5 miles from one another, so the effect of distance is modest. Furthermore, these three hospitals, and especially French Hospital and Sierra Vista, are similar on all observable characteristics.

The pattern disappears for the hospitals out of town. Arroyo Grande is about twelve miles from the three central hospitals, and Twin Cities is a little under twenty miles distant. Their cross-price elasticities with the three central hospitals are substantially below what the logit model would provide. Marion Medical and Valley Community have high cross elasticities and are about 1.5 miles apart.

TABLE 7 Price Elasticities, San Luis Obispo County

Hosptial	French	General	Sierra Vista	Arroyo Grande	Twin Cities	Marian Medical Center	Valley Community
French Hospital	−4.17	.17	2.35	.22	.53	.16	.20
General	1.38	−5.37	2.27	.24	.46	.16	.21
Sierra Vista	1.47	.17	−2.84	.18	.61	.13	.16
Arroyo Grande	1.11	.14	1.50	−3.69	.05	.57	.72
Twin Cities	.72	.08	1.32	.01	−2.30	.01	.01
Marian Medical Center	.22	.02	.27	.15	.00	−2.63	2.08
Valley Community	.19	.02	.24	.13	.00	1.49	−3.45

TABLE 8 Merger Simulation, San Luis Obispo County

			Post-Merger p		
			Divestiture		
Hospital	Owner	p	No	Yes	NFP
French Hospital	Ornda	4,434	6,784	4,467	6,697
General	County	4,577	4,784	4,607	4,753
Sierra Vista	Tenet	4,134	5,469	4,202	5,437
Arroyo Grande	Vista	3,477	3,654	3,712	3,654
Twin Cities	Tenet	4,216	5,587	4,261	5,587
Marian Medical Center	Catholic	3,289	3,331	3,319	3,331
Valley Community	Ornda	4,439	4,552	4,512	4,552

□ **Results.** We use the demand estimates and marginal costs from the model to simulate the equilibrium prices that would result from the merger scenarios described above. Recall that elements of the matrix Θ in the pricing equation take the value one if two hospitals are jointly owned to reflect joint profit maximization and zero if they are independent. The merger is simulated by changing the values of the relevant elements of Θ, and the changes in ownership type are simulated by changing the values of the FP and NFP vectors. After the changes, the 374 nonlinear pricing equations are solved simultaneously for a new price equilibrium.[29] In Table 8, we present the simulated effects of the merger on the hospitals in and around San Luis Obispo County. The columns, beginning with the third, are the observed price in the data, the simulated price after the Tenet/Ornda merger with no divestiture, the simulated price after the Tenet/Ornda merger with divestiture of French Hospital to Vista, and the simulated price after the Tenet/Ornda merger assuming no divestiture and that Tenet and Ornda are not-for-profit.[30]

The findings summarized in this table are that the Tenet/Ornda merger without the divestiture leads to a large price increase at the Tenet and Ornda hospitals in the county: 53% at French Hospital, 32% at Sierra Vista, and 33% at Twin Cities. The competing hospitals saw smaller price increases, 5% at both General and Arroyo Grande.

[29] We solved the system of equations by linearizing demand at the presimulation price vector, solving explicitly for the new price vector (see Gaynor and Vogt, 2003, for the formula in the linear case). Then we recalculated demand at the new price vector (using the estimated logit model), linearized again, and continued iterating until we reached a solution.

[30] Notice that when we change the ownership of these hospitals to not-for-profit, we do not change their behavioral marginal costs or their demand curves, only their scale economies. The objective of the exercise is to test whether otherwise observationally equivalent hospital mergers are different if the ownership of the hospitals is for-profit or not-for-profit.

TABLE 9 Merger Simulation By Location

			Post-Merger p		
			Divestiture		
Area	Owner	p	No	Yes	NFP
San Luis Obispo	Tenet/Ornda	4,238	5,636	4,293	5,615
	All	4,199	5,260	4,271	5,247
Los Angeles	Tenet/Ornda	4,671	4,706	4,706	4,706
	All	4,274	4,277	4,276	4,277
San Diego	Tenet/Ornda	3,596	3,609	3,609	3,609
	All	3,932	3,933	3,933	3,933
Remainder	Tenet/Ornda	4,699	4,716	4,714	4,716
	All	4,650	4,650	4,651	4,650

By contrast, with the divestiture of French Hospital, the price increases were very small at less than 2% for each of the hospitals. Moreover, changing the ownership of the chains to not-for-profit has virtually no effect on the postmerger price increase, as the not-for-profit Tenet/Ornda firm raises its prices by roughly the same amount as the for-profit Tenet/Ornda.

In Table 9, we look at the price effects statewide. Here, we report the same columns. The entries in the table, however, are quantity-weighted prices at the hospitals in each geographic unit. For example, $5,636 is the quantity-weighted average price for Tenet/Ornda hospitals postmerger in San Luis Obispo County for the no-divestiture merger, and $5,260 is the postmerger quantity-weighted average price at non-Tenet/Ornda hospitals in San Luis Obispo County for the no-divestiture merger.

These results confirm the previous analysis that there would have been a strong effect in San Luis Obispo County of this merger absent the divestiture. In addition, the table shows that the merger has little effect on statewide prices or on prices in either Los Angeles or San Diego counties. The small effect for the remainder of the state comes principally from Valley Community (see Table 6), which is near but not in San Luis Obispo County.

8. Conclusion

■ In this article we estimate a structural model of hospital competition and use the estimates to simulate the effect of a merger. We take advantage of detailed microdata on individuals and firms to estimate demand and supply. We find that hospitals face significant, but not large, elasticities of demand for their services. Not-for-profit hospitals set lower prices but have higher markups than do for-profits, due to lower behavioral marginal costs. Our merger simulation reveals no difference between not-for-profits and for-profits in their willingness to exploit merger-created market power. In particular, the merger we simulate was one in which the FTC intervened and forced divestiture of one of the hospitals belonging to the merging firms. Our simulations show postmerger price increases of up to 53% absent the FTC's intervention.

This article provides more evidence on the nature of competition in differentiated-product oligopoly industries, and a particularly important industry at that. Spatial differentiation is important in this industry and bestows market power upon firms.

These results have important implications for policy. Thus far, U.S. antitrust enforcement agencies have not treated not-for-profit hospital mergers differently. Not-for-profits have defended themselves by claiming that because their objective is to benefit the community, they would not exploit any market power gained as a result of merger. The courts have been sympathetic to this view and have rejected government requests to block mergers between not-for-profit hospitals. Our results indicate that this, at least on average for the hospitals in our data, is not correct.

Appendix

TABLE A1 First-Stage Regression for 2SLS Estimates of Demand Equation Dependent Variable = Price in $1000s

Variable	Estimate
Constant	2.38 (.64)
$D_j/(\partial D_j/\partial p_j)^{IV}$	.12 (.04)
W	2.20 (.63)
D^{IV}	-4.89×10^{-5} (7.87×10^{-5})
FP	.20 (.26)
NFP	−.29 (.23)
Teach	.74 (.26)
Tech Index	-1.22×10^{-3} (1.78×10^{-2})
R^2	.086
F	4.91
N	374

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