Competition Among Hospitals

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Abstract

Our objective is to determine the effect of ownership type (for-profit, not-for-profit, government) on firm conduct in hospital markets. Secondary objectives include estimating hospital demand systems useful for market definition and merger simulation. To this end, we estimate a structural model of demand and pricing in the short term hospital industry in California, and then use the estimates to simulate the effect of a merger. Demand is modeled at the level of individual consumers using discrete choice techniques and micro data on individuals. Price in the demand equation is endogenous, and we use recently developed instrumental variables techniques to correct for this. [redacted]e allow the behavior of for-profit and not-for-profit firms to differ, modeling these differences structurally following the relevant theory literature. [redacted]e find that California hospitals in 1995 faced a downward-sloping demand for their products, with an average price elasticity of demand of -5.67. 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 than those of for-profits. [redacted]e simulate the effects of the 1997 merger of two hospital chains. In relatively unconcentrated markets such as Los Angeles and San Diego, the merger has virtually no effect on prices. However, in San Luis Obispo County, where the merger creates a near monopoly, prices rise by up to 58%, and the predicted price increase would not be substantially smaller were the chains to be not-for-profit.

1 Introduction

One of the most important industries in the United States economy is health care, accounting for over one trillion dollars in e penditure annually. This industry is also one in which competition is a real issue, given the e tensive 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 (Jaklevof t [illegible] y [illegible], aas www [illegible] etition [illegible]

Pakes, in particular, have developed econometric models for estimating models of differentiated product oligopoly (Berry, 1994; Berry et al., 1995, 1998). These models have been applied to a variety of industries: automobiles (Berry et al., 1995), (Berry et al., 1998), ready-to-eat breakfast

1994), so we will not offer a further review here. There is more variation in the results of the small number of studies which e amine this relationship for NFPs and FPs separately, however. Three of these papers find that both NFP and FP hospitals set higher prices in more concentrated markets (Dranove and Ludwick, 1999; Keeler et al., 1999; Simpson and Shin, 1997). Two others, however, find that NFP hospitals set lower prices in more concentrated markets, while FPs set higher prices (Lynk, 1995; Lynk and Neumann, 1999). While 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 modeling makes it e tremely difficult to sort out the differences in results between the studies of NFP 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.

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 et al. (2001b) each use their demand systems to calculate measures of the marginal value of adding each 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 et al. (2001b) regress their marginal value measure on hospital profit margins and similarly find a positive relationship. Capps et al. (2001a), in an approach similar to ours, use their demand estimates to simulate mergers and find that mergers of hospitals even in markets which look quite "competitive" by conventional antitrust methods would nevertheless lead to large price increases. Our work is differentiated from this literature primarily by our focus on the effects of not-for-profit status on pricing.

In this paper we estimate a structural model of hospital conduct, treating hospitals as operating in a differentiated product oligopoly and e plicitly developing a model of hospital NFP vs. FP behavior. As part of this e ercise, we estimate the demand for hospital services. We also estimate a pricing equation, and recover marginal cost parameters. Last, we use these estimates to simulate the effects of a merger. We simulate the effect of a merger between two hospital systems in Catof a

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contains our Results. In section 6, we report a merger simulation highlighting the FP/NFP distinction. A conclusion is contained in Section 7.

2 Model

[redacted]e model hospital markets as a differentiated product oligopoly. Since our goal is a structural, estimable, model of demand and supply, we lay characteristics of consumer i are R_i. The functions u and v are assumed to be well-behaved utility functions.

2.1.1 HMO Consumers

Typically, however, consumers do not bear the cost of their hospitalization directly, as either all or most of the cost is borne by an insurer. Similarly, consumers' choices of both which hospital to patronize and what care to consume are determined substantially by their insurer through selective contracting and utilization review.[6] This is especially true of HMO patients who often pay little or nothing when they consume care and whose utilization is often heavily managed by the HMO.[7] Hence, we model the HMO's choices.

[redacted]e posit a very simple model of HMO behavior. HMOs sell policies to consumers, consisting of a premium, M, and decision rules specifying the hospital to which a consumer will be sent and the quantity of care he will be provided, depending on his characteristics, R_i. [redacted]e will denote the hospital-choice decision rule by a J-vector of indicator functions $\chi(R_i)$, where a 1 in the jth place indicates that a consumer with characteristics R_i is sent to hospital j. [redacted]e will write the jth function in this vector for the ith consumer in the mnemonically convenient notation, $\chi_{i \to j}$. The decision rule for quantity of care consumed is $q(R_i)$. [redacted]e assume that R_i is unobservable e ante, so that the consumer evaluates the desirability of the HMO by its premium and its average quality, $\overline{v} = \int_{R_i} \sum_{j=1}^{J} \chi_j\left(R_i\right) v\left(q(R_i), R_i, S_j\right) dF_{R_i}$, i.e., the average utility across consumers from consuming hospital care.

[6] Consumers are also influenced by the advice of their doctors, who in turn are also often influenced by incentives from the insurer. We do not model the doctor-patient interaction here.

[7] HMOs [illegible].

Thus each HMO contract is characterized, for the consumers' purposes, by a pair, $(M, \bar{v})$. Different consumers choose different policies since their incomes differ. [redacted]e are agnostic about the insurance market — by some means, $(M, \bar{v})$ are chosen for each insurer and consumers are allocated among them.[8]

The HMO must choose rules to assign consumers to hospitals, $\chi(R_i)$ and rules to assign quantities, $q(R_i)$. It does this to minimize costs subject to producing its chosen level of quality:

$$min_{\chi(\bullet),q(\bullet)} \int_{R_i} \sum_j \chi_j \left(R_i\right) p_j q(R_i) dF_{R_i}$$

$$s.t. \quad \int \sum_j v(q_i, R_i, S_j) dF_{R_i} \geq \bar{v}. \tag{2}$$

Assuming that a solution e ists, this problem is equivalent to solving the following problem for each consumer individually (where λ is chosen such that the constraint is satisfied at the solution):[9]

$$min_{\chi,q} \sum_j p_j q - \lambda v(q, R_i, S_j) \tag{3}$$

Naturally, λ will vary among health plans and on consumer e ante observables, as

[8]We are assuming that the allocation is independent of consumer characteristics observable to the market participants but unobservable to the econometrician. We have not specified ex ante observable consumer characteristics in our model, however there certainly are such factors that affect M and $\overline{v}$, e.g., age and sex. Therefore this analysis should be thought of as conditional on ex ante observables. When we discuss the solution below, it will also be conditional on ex ante observables. We are assuming, therefore, that HMOs can "price discriminate" among consumers with different observables and that they can offer them, either implicitly or explicitly, different decision rules in their benefits.

[9]For a proof, see the Appendix.

different plans will choose to offer different levels of quality depending on local market conditions and the niche they wish to target.

[redacted]e might just as well think of this problem as one of ma imizing an “effective”

$$D_j(p) = \int_{V_{ij}^* \geq max_j\{V_{ij}^*\}} q_{ij}^* dF_{R_i}. \tag{8}$$

[redacted]e have characterized consumers with HMO insurance and the attendant demand facing hospitals from these consumers. [redacted]e now turn to consumers with “traditional” insurance.

2.1.2 Traditional Insurance Consumers

[redacted]e also model traditional insurance in a simple way. [redacted]ith traditional insurance (also referred to as “conventional,” ”fee-for-service,” or “indemnity”) consumers pay a premium and agree to pay a proportion of e penses (called “coinsurance”). The consumer is then m [redacted]

$$U_{ij} \approx u(I-M) - u'(I-M)\tau p_j q_{ij} + v(q_{ij}, R_i, S_j) \tag{10}$$

Thus, we are effectively assuming either that marginal utility is constant in C or that $\tau p_j q_{ij}$ is small relative to $I - M$. Either way, we still permit the marginal utility of income to vary among consumers. This assumption serves the purpose of leading the effective utility function to have the same structure as in the HMO case for our purposes (i.e. $u'\tau = 1/\lambda$) — although from the perspective of the consumer, there is a difference. This then leads to a hospital's e pected demand in the same way as in the previous section.

2.2 Production and Conduct

Hospitals ("plants" or "brands") in our model produce a single output, inpatient hospital care, for which they charge a single price.[10] 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:

$$\pi_j = p_j D_j(p) - C(D_j(p); Z_j, \zeta_j, W) \tag{11}$$

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

[10] A number of firms in this industry are multihospital systems, hence we treat individual hospitals as plants or brands.

$$p_j = \frac{C_j}{D_j} - \frac{D_j}{\frac{\partial D_j}{\partial p_j}} \tag{12}$$

Many hospital firms are NFP, and the theoretical literature typically deals with this by assuming that hospitals ma imize a utility function, subject to a break-even constraint. A typical characterization is that NFP hospitals have a mission of providing care to the community. We capture this by specifying the utility function for NFPs as depending on quantity produced. We also include profits as an argument to capture any other objectives NFPs may have, thus $U_{NFP} = U(\pi, D)$. Hospitals then choose price to solve:

$$max_p \; U(\pi, D)$$

$$s.t. \; \pi \geq \pi_L$$

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

$$p_j = \frac{C_j}{D_j} + \frac{\frac{\partial U_j}{\partial D_j}}{\frac{\partial U_j}{\partial \pi_j} + \mu_j} - \frac{D_j}{\frac{\partial D_j}{\partial p_j}} \tag{13}$$

This equation suggests that the principal behavioral difference between FP and NFP firms is that NFP firms behave like FP firms with different cost functions (differing by the utility term – the second term in the e pression above). This insight (due to Lakdawalla and Philipson, 1998) is formally correct in our setting with the additional assumptions that: 1) the marginal utility of profit is constant, and 2) the profit constraint does not bind. Under those conditions, NFPs behave e actly like FPs, e cept with different cost functions. Setting the marginal utility of profits to 1 (without further loss of generality), the previous equation reduces to:

$$p_j = \frac{C_j}{D_j} + \frac{U_j}{D_j}(D_j) - \frac{D_j}{\frac{\partial D_j}{\partial p_j}} \tag{14}$$

This property has the benefit that standard techniques now may be applied to the NFP firms. The disadvantage is that (using the pricing equation) we cannot separately identify differences in goals between FP and NFP firms from differences in costs between the two forms.[11] Hereafter, we will speak of "behavioral" marginal costs, which we will denote $\frac{\partial C^B}{\partial D}$, meaning $\frac{\partial C}{\partial D}$ for FP and $\frac{\partial C}{\partial D} + \frac{\partial U}{\partial D}$ for NFP.

Multi-plant 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 $J \times J$ matri with $\Theta_{jk} = 1$ if hospitals j and k have the same owner and $\Theta_{jk} = 0$ otherwise. Under our maintained Bertrand assumption, the pricing equation for hospital j, part of a multihospital system, is then:

$$0 = D_j + \left(p_j - \frac{C_j^B}{D_j}\right) \frac{D_j}{p_j} + \sum_{j' sameowner} \left(p_{j'} - \frac{C_{j'}^B}{D_{j'}}\right) \frac{D_{j'}}{p_j} \tag{15}$$

Denote by $\left[\frac{\partial D}{\partial p}\right]$ the $J \times J$ demand derivative matri . Stacking up these pricing equations,

[11] NFP and FP firms are likely to have different costs because of their different access to capital markets. FPs can raise capital through equity issue, while NFPs cannot. However, NFPs can often issue tax-advantaged debt.

solving for price, and denoting element-by-element (Hadamard) matri multiplication by $\circledast$ yields:

$$P = \left[\frac{C^B}{D} \right] + \quad \Theta \circledast \left[\frac{D}{p} \right] \Big\}^{-1} D \tag{16}$$

[redacted]e have now characterized demand and supply, which form the basis for our econometric model.

3 Econometric Specification & Estimation

[redacted]e proceed in several subsections. First, we impose functional forms, derive some useful results, and discuss identification for the consumer side of the model. Then, we briefly describe the functional form imposed on the producer side.

3.1 Demand

Observable consumer characteristics are denoted by X and observable hospital characteristics are denoted by Z. There are L observable consumer characteristics and K observable hospital characteristics. Distance between a consumer's residence and the hospital is denoted d

3.1.1 Functional Form

[redacted]e use the following functional form for the effective utility function, V:

$$
\begin{aligned}
V_{ij} &= -\tilde{\alpha}_i^p p_j q_{ij} + \frac{1}{\gamma}\left(\tilde{\beta}_i q\right)^{\gamma} \\
&+ \tilde{\alpha}_i^d d_{i\to j} + \tilde{\alpha}_i^{d^2} d_{i\to j}^2 \\
&+ \sum_{k=1}^{K} Z_{jk}\tilde{\alpha_{ik}} + \xi_j + \epsilon_{ij} \qquad (18)
\end{aligned}
$$

$$
\begin{aligned}
\tilde{\beta}_i &= exp\left(\sum_{l=1}^{L} X_{il}\beta_l + \nu_i\right) \\
\tilde{\alpha}_i^p &= exp\left(\alpha_0^p + \sum_{l=1}^{L} X_{il}\alpha_l^p\right) \\
\tilde{\alpha}_i^d &= \alpha_0^d + \sum_{l=1}^{L} X_{il}\alpha_l^d \\
\tilde{\alpha}_i^{d^2} &= \alpha_0^{d^2} + \sum_{l=1}^{L} X_{il}\alpha_l^{d^2} \\
\tilde{\alpha}_{ik} &= \alpha_0 + \sum_{l=1}^{L} X_{il}\alpha_{lk}
\end{aligned}
$$

Here ϵ_{ij} is an i.i.d. [redacted]eibull random variable. In much of the previous literature, the equivalents of our α and β coefficients have been modeled using random coefficients methods (beginning with Berry et al., 1995). Absent individual heterogeneity, popular discrete consumer choice models have the undesirable property of a fi ed relationship between market shares and own and cross price elasticities of demand (see Berry, 1994).[12] 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 e plicitly account for observable individual heterogeneity. Distance in particular has been shown to be one of the most important determinants of choice of hospital.[13] In our model hospitals physically close to one another have much higher cross-price elasticities than do hospitals far apart, breaking the infle ible relationship between market share and elasticity. Separately, the specification, even as it is, is e tremely computationally burdensome, given the nearly 1 million observations used to estimate the over 400 parameters of the discrete choice model.

3.1.2 Consumption and Indirect Effecti e Utility

From this function, the optimal quantity which would be consumed by i were he to go to j is:

$$q_{ij}^{*} = \beta_i^{\frac{\gamma}{1-\gamma}} \alpha_i^{\frac{1}{\gamma-1}} p_j^{\frac{1}{\gamma-1}} \tag{19}$$

It is also easy to solve for the indirect utility of choosing hospital j:

[12] 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.

[13] 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).

$$
\begin{aligned}
V_{ij}^{*} &= \left(\frac{1-\gamma}{\gamma}\right)\beta_i^{\frac{\gamma}{1-\gamma}}\alpha_i^{\frac{\gamma}{\gamma-1}}p_j^{\frac{\gamma}{\gamma-1}} \\
&+ \tilde{\alpha}_i^{d}d_{i\to j}+\tilde{\alpha}_i^{d^2}d_{i\to j}^{2} \\
&+ \sum_{k=1}^{K} Z_{jk}\tilde{\alpha}_i k+\xi_j+\epsilon_{ij} \qquad (20)
\end{aligned}
$$

However, to reflect the fact that information is acquired during a hospital stay about the consumer's need for care, we will assume that ν_i is independent of ϵ and unobservable to both the demand and supply sides of the market before the choice of hospital is made. E pected indirect utility becomes:

$$
\begin{aligned}
EV_{ij}^{*} &= \left(\frac{1-\gamma}{\gamma}\right)E(\beta_i^{\frac{\gamma}{1-\gamma}})\alpha_i^{\frac{\gamma}{\gamma-1}}p_j^{\frac{\gamma}{\gamma-1}} \\
&+ \tilde{\alpha}_i^{d}d_{i\to j}+\tilde{\alpha}_i^{d^2}d_{i\to j}^{2} \\
&+ \sum_{k=1}^{K} Z_{jk}\tilde{\alpha}_i k+\xi_j+\epsilon_{ij} \qquad (21)
\end{aligned}
$$

Now, assuming that ν_i is identically distributed among consumers, the e pectation, $E\left(exp\left(\frac{\gamma}{1-\gamma}\nu_i\right)\right)$, is simply absorbed into the intercep

3.1.3 Indirect Effecti e Utility and Expenditure

In the model we presented in section 2, we assumed that we observe the price of care at each hospital and the quantity of care demanded by each consumer. Neither of these things is true in our data. What we observe is list e penditures for each patient ("charges") — the e penditures which would apply were they to pay list prices. In addition, we observe the average ratio of actual e penditures at a hospital to the list e penditures (see equation 38 below). What we can make from this is an estimate of actual e penditures for each patient. Needless to say, this likely introduces measurement error. In addition, we do not really want to know e penditure by each consumer, we want to know the price paid and the quantity consumed by each patient.

In the data, we observe neither p nor q. We observe only $p_j q^*_{ij}$ for the hospital actually chosen. This makes calculation of the first term of equation 20 problematic. However, since $p_j q^*_{ij} = \beta_i^{\frac{\gamma}{1-\gamma}} \alpha_i^{\frac{1}{\gamma-1}} p_j^{\frac{\gamma}{\gamma-1}}$, the first term of equation 20 is $\frac{1-\gamma}{\gamma}\alpha_i^p p_j q^*_{ij}$. So, if $p_j q^*_{ij}$ were to be known for each i and j, then $\frac{1-\gamma}{\gamma}\alpha_i^p$ would be estimable. Now, only $p_j q^*_{ij}$ for the chosen j is data, so we turn to the question of constructing $p_j q_{ij}$ for the unchosen j.

Consider that, as things are parameterized now:

$$\begin{aligned}
\ln p_j q^*_{ij} &= \frac{\gamma}{1-\gamma}\ln\tilde{\beta}_i + \frac{\gamma}{\gamma-1}\ln p_j + \frac{1}{\gamma-1}\ln\tilde{\alpha}_i^p \\
&= \sum_j \chi_{i\to j}\frac{\gamma}{1-\gamma}\ln p_j \\
&+ \frac{1}{\gamma-1}\sum_l X_{il}\left(\gamma\beta_l + \alpha_l^p\right) + (\gamma\nu_i) \qquad (22)
\end{aligned}$$

If we have $p_j q_{ij}$ and wish to calculate $p_{j'} q^*_{ij'}$, the formula is:

$$p_{j'} q^*_{ij'} \quad = \quad p_j q^*_{ij} exp\left(\frac{\gamma}{\gamma - 1}\left(\ln p_{j'} - lnp_j\right)\right)$$

α and γ. To deal with this, we will assume that $\gamma = \infty$, equivalently that the elasticity of demand for hospital care, once a consumer has arrived at a hospital, is zero. This is a reasonable assumption, based on the results of the RAND Health Insurance E periment. The findings of that e periment included 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). With this assumption in place, equation 22 becomes:

$$\begin{aligned} \ln p_j q^*_{ij} &= \sum_j \chi_{i \to j} \ln p_j \\ &+ \sum_l X_{il} \beta_l + \nu_i \end{aligned} \tag{25}$$

Beginning with this equation, we may separate price and quantity. Once it is estimated, we may fi X_i at some value (we take means) and define $E(q_i) = 1$ for that X_i. Then, equation 25 can be used to predict e pected e penditures for this "standard" discharge, giving a measure of p for each hospital.

3.1.5 Estimating Equations

As we describe above, the demand model has the utility for consumer i of going to hospital j as a function of hospital characteristics, K observable and one unobservable, and of interactions between hospital and L observable consumer characteristics. We rewrite and slightly generalize equation 24, absorbing the hospital's price into Z_j and $\hat{q}$ into X_i:

$$\begin{aligned} EV_{ij}^* &= \sum_{k=1}^{K} Z_{jk}\alpha_{ik} + \xi_j \\ &+ \rho d_{i\to j} + \sum_{l=1}^{L} \rho_l^X X_{il} d_{i\to j} + \sum_{k=1}^{K} \rho_k^Z Z_j k d_{i\to j} \\ &+ \rho^2 d_{i\to j}^2 + \sum_{l=1}^{L} \rho_l^{2X} X_{il} d_{i\to j}^2 + \sum_{k=1}^{K} \rho_k^{2Z} Z_j k d_{i\to j}^2 + \epsilon_{ij} \qquad (26) \\ \alpha_{ik} &= \alpha_{0k} + \sum_{l=1}^{L} X_{il}\alpha_{lk} \qquad (27) \end{aligned}$$

Berry et al. (1998) discuss the estimation of models in this class using micro data. First, we substitute equation 27 into 26 to get:

$$\begin{aligned} EV_{ij}^* &= \sum_{k=1}^{K} \alpha_{0k} Z_{jk} + \sum_{k=1}^{K}\sum_{l=1}^{L} X_{il} Z_{jk}\alpha_{lk} + \xi_j \\ &+ \rho d_{i\to j} + \sum_{l=1}^{L} \rho_l^X X_{il} d_{i\to j} + \sum_{k=1}^{K} \rho_k^Z Z_j k d_{i\to j} \\ &+ \rho^2 d_{i\to j}^2 + \sum_{l=1}^{L} \rho_l^{2X} X_{il} d_{i\to j}^2 + \sum_{k=1}^{K} \rho_k^{2Z} Z_j k d_{i\to j}^2 + \epsilon_{ij} \qquad (28) \end{aligned}$$

It is tempting to estimate equation 28 using a logit ma imum likelihood routine. However, under virtually any oligopoly model of price setting, p_j (one of the Z_j) will be corrξ_j

E

terms involving price, so that D_j^{IV} depends only upon e ogenous distances and interactions between consumer and producer characteristics. In a similar manner, an instrument for $\frac{D_j}{\frac{\partial D_j}{\partial p_j}}$ can be calculated.[14] These instruments are similar to Berry et al. (1998), who use predictions of the markup as instruments.

3.2 Supply

Recall the pricing equation:

$$P = \left[\frac{C^B}{D}\right] + \quad \Theta \circledast \left[\frac{D}{p}\right]\Bigg\}^{-1} D \tag{34}$$

After estimating the demand side, we can calculate

$$\Theta \circledast \left[\frac{D}{p}\right]\Bigg\}^{-1} D.$$

Representative elements of $\left[\frac{\partial D}{\partial p}\right]$ are calculated as follows:

$$\frac{D_j}{p_j} = \sum_{i=1}^{I} Pr\{i \to j\}(1 - Pr\{i \to j\})q_{ij} \tag{35}$$

$$\frac{D_j}{p_j'} = \sum_{i=1}^{I} Pr\{i \to j\}Pr\{i \to j'\}q_{ij} \tag{36}$$

Thus, our estimating equation for the supply side is:

[14] Before estimating equation 30, we do not know the value of $\overline{\alpha}$. We create D^{IV} and $\frac{D_j}{\frac{\partial D_j}{\partial p_j}}^{IV}$ by first setting $\delta = 0$ and the parameters on price in the interacted logit to zero. Then, with estimates of $\overline{\alpha}$ in hand, we calculate the instruments as described above.

$$P - \quad \Theta \circledast \left[\frac{D}{p} \right] \Big\}^{-1} D = \left[\frac{C^B}{D} \right]$$

$$P - \quad \Theta \circledast \left[\frac{D}{p} \right] \Big\}^{-1} D = \omega_0 + D\omega_D + W\omega_W + Z\omega_Z + \zeta \tag{37}$$

D is endogenous, but the other variables are assumed e ogenous. Again, D_j^{IV} is used for instrumenting, as it depends only upon presumed e ogenous location.

3.3 Estimation Procedure

The estimation proceeds in four steps. First, the e penditure equation (25) is estimated via OLS. From this p and q are backed out and used in the ne t step, which is the estimation of the multinomial logit demand system (29) by ma imum 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 (30), estimated by two stage least squares. Finally, the parameters from the demand estimation are used to calculate the left-hand-side of (37), and it is estimated via two stage least squares.

4 Data

The California Office of Statewide Health Planning and Development (OSHPD)[15] maintains a variety of datasets on various aspects of health care in California. Each of the particular datasets we draw upon, and the criteria for selecting data subsets is described below.

4.1 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 e amine because it is during the time 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 occurrence of the merger whose effects we simulate.

4.1.1 Discharge Data

Each non-Federal 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, se , race), diagnosis (several DRG and ICD9-CM codes),[16] treatment (several ICD9-CM codes), an identifier for the hospital at which the patient sought care, the patient's zipcode of residence, and charges.

Charges are the "list" price for the hospital stay. They are typically presented on a

[15] http://www.oshpd.cahwnet.gov
[16] DRG (

hospital bill as a sum of items multiplied by a list price for each item.[17] The charges which appear on a patient's discharge record are a poor pro y 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 which are reductions from charges.[18] As a consequence, charges *per se* cannot be used as a measure of transaction price; although, given the way they are calculated they are related to the amount of care which a patient consumes.

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.

4.1.2 Financial Data

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

These reports contain quite e tensive 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

[17] The line-item bill is not observable to us, only the total charges are.

[18] At the time of our data, in California, there were a variety of different reimbursement arrangements among insurers and hospitals. Some insurers pay a negotiated discount off charges. Some pay a negotiated flat per day (called a "*per diem*"). Some pay an amount per discharge, based upon the diagnosis. Some pay

teaching hospital or not, and wages. Since we are only using hospital characteristics, which are fi ed, and wages, which change slowly over the

Table 1: Distribution of Discharges by Insurance

Insurance Type	Frequency	Percent
Medicare	1,023,160	28.2%
Medicaid	960,811	26.5%
HMO	780,801	21.5%
PPO	336,913	9.3%
Other Pvt	145,161	4.0%
Self Pay	135,406	3.7%
BC / BS	7[redacted]	
	[redacted]	

values for any of the variables used in any of our analyses or with charges less than 500 or greater than 500,000 are e cluded, as are consumers with lengths of stay of 0 or of greater than 30. After all the e clusions, there are 913,660 remaining observations.[20]

There are 593 total hospitals in the financial data. Of these, 420 are short-term general hospitals (this e cludes 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 e ample).[21] 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 e cluded.[22] Finally, we e clude hospitals with fewer than 100 discharges for the year. This leaves us with an analysis sample of 913,660 discharges and 374 hospitals.

4.3 Location

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 for each California zip code appearing in our data from census files. For the hospitals, we obtained each one's longitude and

Table 2: Variable Descriptions

Name	Description	Mean	Std dev
X	**Consumer Characteristics**		
$\hat{q}$	E(quantity)from eqn 25	1.24	1.61
HMO	Membership in HMO	0.50	0.50
PPO	Membership in PPO	0.31	0.46
unsched	Unscheduled admission	0.53	0.50
X	**Distance**		
$d_{i\to j}$	Distance to (chosen) hospital (miles)	11.56	27.78
$d^2_{i\to j}$	Distance squared		
Z	**Hospital Characteristics**		
P	E(Price) from eqn 25	4696	1603
FP	For-profit status	0.28	0.45
NFP	Not-for-profit status	0.52	0.50
Teach	Teaching hospital	0.21	0.41
Tech	Technology inde	15.02	6.06
SYS	Multihospital system member	0.49	0.50
W	**Input Price**[illegible]		

5 Results

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

5.1 Prices and Quantities

Equation 25 is estimated on the set of 913,660 discharges from the 374 analysis hospitals. The regression is run with log net e penditure 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 se categories, 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 between 23 variables for major diagnostic category (a more granular measure of diagnosis) and the age, se , race, severity, type of admission, and other diagnoses dummies. There are 1792 right-hand-side variables total. The R^2 for the equation is 0.81.

We can now calculate price and quantity as described previously using the estimates from this regression. The average hospital price is $4,696 with a standard deviation of $1,603 among the 374 hospitals. Government hospitals have the highest prices (recall, on private-pay patients), at $4957 per adjusted discharge. FP hospitals have higher prices ($4793) than do NFP hospitals ($4545). Quantity per consumer is highest at NFP at 1.24

adjusted discharges per discharge. FPs have 1.20 adjusted discharges per discharge, and government hospitals have 1.11.[23]

5.2 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 5 hospital characteristics and the 4 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 Tables 3 and 4 (omitting the coefficients

Table 4: MNL Results, continued

Variable	Estimate	Standard Error
$d_{i \to j}$	-23.92	0.05
$d_{i \to j}^2$	3.15	0.01
$d_{i \to j}\ \hat{q}$	0.717	0.003
$d_{i \to j}^2\ \hat{q}$	-0.119	0.001
$d_{i \to j}$ HMO	-6.517	0.018
$d_{i \to j}^2$ HMO	1.023	0.003
$d_{i \to j}$ PPO	-2.860	0.017
$d_{i \to j}^2$ PPO	0.412	0.003
$d_{i \to j}$ unsch	-1.909	0.014
$d_{i \to j}^2$ unsch	0.314	0.003
$d_{i \to j}$ P	0.596	0.005
$d_{i \to j}^2$ P	-0.069	0.002
$d_{i \to j}$ FP	0.621	0.035
$d_{i \to j}^2$ FP	-0.080	0.008
$d_{i \to j}$ NFP	0.280	0.029
$d_{i \to j}^2$ NFP	-0.022	0.007
$d_{i \to j}$ Teach	4.06	0.019
$d_{i \to j}^2$ Teach	-0.583	0.005
$d_{i \to j}$ Tech	0.048	0.002
$d_{i \to j}^2$ Tech	-0.004	0.001

Table 5: Demand Equation

Variable	OLS	2SLS
constant	-1.92	1.40
	(0. 3)	(1.84)
P	-0.52	-1.22
	(0.08)	(0.38)
FP	3.16	3.15
	(0.36)	(0.40)
NFP	1.54	
	(0.34)	

OLS produces an estimate of the coefficient on price of the “right” sign. However, as we move across the table and add instruments, 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 -5.67. The elasticity is highest for FP firms, at -6.25 and lowest for government hospitals at -5.21. NFP hospitals on average face an elasticity of -5.54. As indicated by the estimates for the relevant dummy variables, on average, consumers prefer FP to NFP hospit coe

Table 6: Supply Equation

Variable	OLS	2SLS
constant	0.21	0.56
	(0.62)	(0.68)
W	3.06	2.70
	(0.63)	(0.68)
D	-0.15	0.12
	(0.11)	(0.19)
$D \times FP$	-0.08	-0.29
	(0.13)	(0.14)
$D \times NFP$	0.08	-0.14
	(0.13)	(0.18)
FP	0.88	1.06
	(0.30)	(0.42)
NFP	-0.10	0.11
	(0.28)	(0.36)
$Teach$	0.91	0.93
	(0.22)	(0.24)
$Tech$	0.04	0.01
	(0.02)	(0.02)
SYS	-0.49	-0.45
	(0.17)	(0.18)
R^2	0.17	
N	374	374

apparent scale diseconomies for NFPs compared to FPs. As we have 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, hosp

Table 7: Means by Ownership Class

Variable	GVT	FP	NFP
δ_j	-1.18	1.83	1.65
p_j	4957	4793	4545
Teach	0.31	0.07	0.25
Tech	12.95	12.25	17.26
W			

Table 8: San Luis Obispo County Hospitals

Hospital	Owner	P	D	Beds	Distance
French	Ornda	4434	2179	147	0.28
General	County	4577	255	46	0.72
Sierra Vista	Tenet	4134	3722	186	0.99
Arroyo Grande	Vista	3477	546	65	12.03
Twin Cities	Tenet	4216	1683	84	19.21
Marian Med Ctr	Catholic	3289	2240	225	26.24
Valley Cmty	Ornda	4439	2313	53	26.79

the three largest. The FTC permitted the merger to go through, but 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 NFP. The idea of the third simulation is to test the theory that NFP 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 8.

The first three hospitals are "in town" in San Luis Obispo; the ne t 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.

6.1 Methodology

entries of 0 for government and not-for-profit hospitals. Similarly for NFP. The intercept of the linearized demand is:

$$D|_{P=0} = D - \frac{D}{P} * P \tag{42}$$

To simulate the merger, we modify Θ appropriately to reflect the new joint ownership and calculate $\hat{P}$:

$$\hat{P} = \left[\frac{C^B}{D}\right] - \quad \Theta \circledast \left[\frac{D}{p}\right]\Big\}^{-1} D$$

$$\hat{P} = \left[\left.\frac{C^B}{D}\right|_{D=0} + \Delta D\right] - \quad \Theta \circledast \left[\frac{D}{p}\right]\Big\}^{-1} D$$

$$\hat{P} = \left.\frac{C^B}{D}\right|_{D=0} + \left(\Delta - \quad \Theta \circledast \left[\frac{D}{p}\right]\Big\}^{-1}\right)\left(D|_{P=0} + \left[\frac{D}{p}\right]\hat{P}\right)$$

$$\hat{P} = \left(I - \left(\Delta - \quad \Theta \circledast \left[\frac{D}{p}\right]\Big\}^{-1}\right)\frac{D}{p}\right)^{-1}\left(\left.\frac{C^B}{D}\right|_{D=0} + \left(\Delta - \quad \Theta \circledast \left[\frac{D}{p}\right]\Big\}^{-1}\right) D|_{P=0}\right)$$

The merger is simulated by changing the values of Θ

Table 9: Merger simulation: San Luis Obispo

Hospital	Owner	P	Post-Merger P Divestiture No	Yes	NFP
French	Ornda	4434	6987	4471	6837
General	County	4577	5546	4608	5513
Sierra Vista	Tenet	4134	6175	4205	6129
Arroyo Grande	Vista	3477	4214	3640	4188
Twin Cities	Tenet	4216	6291	4262	6279
Marian Med Ctr	Cath	3289	3613	3319	3607
Valley Cmty	Ornda	4439	4911	4514	4917

Table 10: Merger simulation: by location

Area	Owner	P	Post-Merger P Divestiture No	Yes	NFP
San Luis Obispo	Tenet/Ornda	4238	6434	4294	6366
	all	4199	6263	4261	6198
Los Angeles	Tenet/Ornda	4671	4702	4702	4691
	all	4274	4278	4278	4277
San Diego	Tenet/Ornda	3596	3613	3613	3610
	all	3932	3934	3934	3934
Remainder	Tenet/Ornda	4699	4740	4714	4739
	all	4650	4655	4651	4655

after the Tenet/Ornda merger with no divestiture, the price after the Tenet/Ornda merger with divestiture of French Hospital to Vista, and the price after the Tenet/Ornda merger assuming no divestiture and that Tenet and Ornda are NFP.[26]

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: 58% at French and 49% at Sierra Vista and Twin Cities. The competing hospitals also saw

[26]Notice, when we change the ownership of these hospitals to NFP, we do not change their behavioral marginal costs, 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 FP or NFP

substantial price increases, 21% at General and at Arroyo Grande.

By contrast, with the divestiture of French Hospital, the price increases were very small at less than two percent for each of the hospitals. Moreover, have higher markups than do FPs, due to lower behavioral marginal costs. Our merger simulation reveals no difference between NFPs and FPs in their willingness to e ploit 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 [illegible]

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A Appendix

Now, integrating both sides over R_i and imposing the constraint:

$$
\begin{aligned}
\int_{R_i} \sum_j \chi_j^* \left(p_j q_i^*\right) - \lambda \overline{v} \quad &\leq \quad \int_{R_i} \sum_j \chi_j \left(p_j q_i\right) - \lambda \overline{v} \\
\int_{R_i} \sum_j \chi_j^* \left(p_j q_i^*\right) \quad &\leq \quad \int_{R_i} \sum_j \chi_j \left(p_j q_i\right)
\end{aligned}
$$

This proves the result. □

A.2 First-Stage Regression Estimates

First-stage regression for average utility 2SLS
(dependent variable = price in \$1000s)

Variable	Estimate
constant	2.38 (0.64)
${\frac{D_j}{\frac{\partial D_j}{\partial p_j}}}^{IV}$	0.12 (0.04)
W	2.20 (0.63)
D^{IV}	-4.89×10^{-5} (7.87×10^{-5})
FP	0.20 (0.26)
NFP	-0.29 (0.23)
Teach	0.74 (0.26)
tech	-1.22×10^{-3} (1.78×10^{-2})