

ROUGH DRAFT: NOT FOR CITATION OR QUOTATION

A COMPETITION INDEX FOR DIFFERENTIATED PRODUCTS OLIGOPOLY WITH AN APPLICATION TO HOSPITAL MARKETS

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ABSTRACT. We develop a competition index for differentiated products oligopoly and apply it to assessing the impact of concentration on price in hospital markets in California. Our index, which we term LOCI, is bounded between zero and one and increases with the competitiveness of a market. We use 1992-1995 hospital data from California to estimate the impact of concentration on price using our new concentration measure. We find that on average, hospital prices decrease significantly as markets are more competitive. A hypothetical merger that decreases the number of firms from 3 to 2 leads to a price increase of \$800, or 16%. The estimated average demand elasticity for hospital services is -3.55 . Government hospitals face a less elastic demand of -3.14 than all ownership types. Demand elasticity for for-profit and not-for-profit hospitals are -4.5 and -3.25 respectively.

1. Introduction

Industrial organization economists have long been interested in the relationship between observed prices and quantities and market power. Initial studies of markets were case studies where researchers described the functioning of a market in qualitative detail. In these case studies, researchers usually uncover trends, patterns and associations. The pioneering work of Bain (1951) subsequently introduced the structure-conduct-performance paradigm (SCP). This paradigm posits that market structure can be used to infer conduct in an industry. The conduct of firms in an industry can then be used to evaluate the performance of that industry. Empirically, researchers who employ this methodology usually regress outcome variables such as price, price-cost margins, or profits on explanatory variables and a measure of concentration. The Herfindahl-Hirschmann Index (HHI)¹ is usually used as the measure of concentration. There are a number of well known criticisms of this paradigm.² First, it assumes that price-cost margins can be easily inferred from accounting data. It is well known that accounting data diverge from economic costs, thus using empirical measures that rely on cost data is problematic (Fisher and McGowan (1983)). Second, it assumes that cross-section variation in industry structure can be captured by a small number of

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¹The HHI is defined as the sum of squared market shares, $HHI = \sum_{i=1}^N s_i^2$.

²See Bresnahan (1989).

observable measures. Researchers are usually interested in the market structure of one industry. Third and more importantly, it fails to address the fact that market structure is endogenous. In fact, the relationship between market structure, conduct and performance may be bi-directional. For instance, higher prices may attract entry, which alters concentration. The concentration of firms in an industry would then appear to affect prices, when in reality the causation runs the other way. Alternatively, conduct may influence entry and exit behavior. Also, observed performance in an industry could be the result of cost heterogeneity, and not conduct or structure.

The approach that has emerged as an alternative to SCP is structural modeling. This approach estimates demand, cost, and pricing equations based on a specific model of competitive conduct. These econometric models have the virtue of being derived from explicit economic models and capture the underlying structure of the economic system. However, they are also usually very complicated and difficult to estimate. Thus, at one end of the spectrum, we have the HHI, which is very easy to calculate once there is data to calculate market share, and SCP econometric models that are easy to estimate. On the other end are structural models that are a better approximation of the underlying economic structure of markets, but are complicated and hard to estimate.

We contribute to this literature by developing a competition index for differentiated oligopoly markets that is easy to calculate and grounded in theory. The index alone can be calculated and used in the same way as is the HHI. There is also an econometric model that uses this index. This econometric model can be derived as the reduced form pricing equation from a full structural model.

Our index is derived to be theoretically justified for differentiated products. To derive our index, we divide consumers into “types” and specify a utility function that treats all consumers of the same type as uniform. Types are defined using observable characteristics of consumers (or a combination of characteristics).³

We use the logit choice model to derive our competition index, which we term LOCI, for LOgit Competition Index. LOCI is bounded between zero and one. For markets where a firm is a monopoly for all consumer types, the LOCI approaches 0 in the limit. For a firm that is in a competitive market for all patient types, LOCI approaches 1 in the limit. We apply the LOCI to hospital data from California for the period 1992-1995. We find that competition as measured by LOCI has a large effect on price. For example, the average effect of a merger between equal sized firms that decreases the number of firms from 3 to 2 is an increase in price of over 16 percent. We

³For example, distance from a seller, age, sex, etc.

also recover the elasticity of demand faced by hospitals. For the average hospital this is -3.55 . For-profit hospitals face more elastic demand, and not-for-profit and public hospitals face less elastic demand.

This paper is organized as follows. Section 2 gives an overview of competition and antitrust in hospital markets. In section 3, derive the LOCI. Section 4 we outline our econometric specification. Section 5 describes our data sources and variables. In section 6, we give a descriptive statistics of our data. Section 7 outlines our results and 8 concludes the paper.

2. Competition and Antitrust Hospital Markets

One of the most important industries in the United States economy is health care, accounting for nearly two trillion dollars in expenditure annually (Smith et al., 2006). The United States relies on markets for health care delivery and financing. As a consequence, antitrust enforcement is an important component of health care policy. This industry 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 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, Pittsburgh, Philadelphia, St. Louis, and San Francisco (and others), have come to be dominated by 2 – 3 large hospital systems. Not surprisingly, many health plans have complained about rising prices as a result of these consolidations (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, and engaged in many activities combating anticompetitive practices.⁴ Prior to 1994, the FTC and the DOJ had considerable success in challenging hospital mergers.⁵ In the eight years that followed the Commission

⁴See <http://www.ftc.gov/> and <http://www.usdoj.gov/> for detailed information.

⁵The government won the following four cases: American Medical International (104 F.T.C. 1, final judgment July, 1984) and Hospital Corporation of America (HCA) (106 F.T.C. 455, final judgment October, 1985), University Health (F.T.C. v. University Health Inc.), 1991-1 Trade Cas. (CCH) 69,444, revd 938 F.2d 1206 (11th Cir. 1991) and Columbia Hospital Corporation (F.T.C. v. Columbia 1993-1 Trade Cas. 70,209, 6 Trade Reg. Rep. 23,399)

and the Department lost seven successive cases involving hospital mergers.⁶ In all merger cases, the government usually calculates the HHI for the market pre and post merger to estimate the effect of consolidation on prices. A major difficulty that the government has faced is defining the relevant geographic market. Since the HHI is dependent on the specification of a relevant product and geographic market, overstating the market will understate the magnitude of the HHI.

The general consensus from empirical studies of competition in hospital markets is that from the late 1980's onwards competition led to lower prices (Zwanziger and Melnick, 1988; Dranove, Shanley and Simon, 1992; Dranove, Shanley and White, 1993; Gruber, 1994). These are all SCP studies covering various geographic areas, time periods, and using varying measures of the HHI (see Vogt and Town, 2006 for an overview). The results of these studies can be used to "predict" the impacts of mergers by calculating the effect of a change in the HHI due to a merger. Vogt and Town (2006) do such a calculation for what they call a "standard merger" – a merger between 2 firms in a market with 5 firms with equal market shares. Such a merger leads to an increase in the HHI from 2,000 to 2,800. They conclude that the strongest evidence from these studies is that such a merger would lead to price increases of about 5 percent.⁷

3. Deriving the Logit Competition Index (LOCI)

We now develop the Logit Competition Index (LOCI) that accounts for the differentiated products markets. We consider a model with multinomial logit demand and observable consumer heterogeneity. This is based on the model in Gaynor and Vogt (2003), which is a version of Berry, Levinsohn, and Pakes (1995), but with observable heterogeneity. Consider a model in which there are $j = 1 \dots J$ firms facing $t = 1 \dots T$ different types of consumers, N_t of each type. A type refers to a group of consumers who have similar preferences for a product. For example, for the automobile industry some types could be: males aged 18-25, couples with 2 or more children under age 7 earning over \$100,000 per year, etc. In the hospital industry, the key differentiating characteristic is distance. There is very strong evidence that consumers do not like to travel far for hospital

⁶These seven cases are: *California v. Sutter Health Sys.*, 84 F. Supp. 2d 1057 (N.D. Cal.), aff'd mem., 2000-1 Trade Cas. (CCH) 87,665 (9th Cir. 2000), revised, 130 F. Supp. 2d 1109 (N.D. Cal. 2001); *FTC v. Tenet Healthcare Corp.*, 17 F. Supp. 2d 937 (E.D. Mo. 1998), rev'd 186 F.3d 1045 (8th Cir. 1999); *United States v. Long Island Jewish Med. Ctr.*, 983 F. Supp. 121 (E.D.N.Y. 1997); *FTC v. Butterworth Health Corp.*, 946 F. Supp. 1285, 1300-1301 (W.D. Mich. 1996), aff'd, 1997-2 Trade Cas. (CCH) 71,863, 71,867-68 (6th Cir. 1997); *United States v. Mercy Health Services*, 902 F. Supp. 968 (N.D. Iowa 1995), vacated as moot, 107 F.3d 632 (8th Cir. 1997); *FTC v. Freeman Hosp.*, 911 F. Supp. 1213 (W.D. Mo.), aff'd, 69 F.3d 260 (8th Cir. 1995); *Ukiah Adventist Hospital v. FTC*, No. 93-70387 (9th Cir. May 18, 1994)

⁷This exercise is not a true merger simulation, because this exercise does not calculate equilibrium price.

services. As a consequence, in this application we will use consumer location as our measure of consumer type.

Write the utility of consumer of firm j for type t as:

$$(1) \quad U_{tj} = -\alpha p_j + a_{tj} + \varepsilon_{tj}$$

We assume the error term, ε_{tj} , is distributed Weibull, so this utility function generates a logit demand system. The effect of observable characteristics is captured nonparametrically in a_{tj} rather than via covariates. The a_{tj} term captures the perceived desirability or attractiveness of firm j to consumers of type t .

In this paper, we define types based on distance, the key hospital product characteristic. We implement this by having types correspond to zip codes. Consumers within a zip code t are assumed to have homogeneous preferences towards the various firms j . In future work we plan to relax this assumption by considering other characteristics such as condition or condition category, insurance type, admission type, or various demographic indicators.

This utility function is less flexible than those typically used in multinomial logit demand systems. In particular, it assumes constant marginal utility of income, and consumer homogeneity within type. On the other hand, the a_{tj} capture characteristics non-parametrically, without the use of covariates.

There are J firms (hospitals), and each firm produces multiple outputs. We assume that output can be expressed as an output index. Each hospital has observable characteristics denoted by Z_j and pays prices W_j for its inputs. A salient characteristic of the hospital industry is the prominence of not-for-profit (NFP) firms. We model NFP hospitals as having the objective of maximizing a utility function that is additively separable in profit and quantity. This allows us to represent NFPs as being like for-profit (FP) firms, but with lower costs (since they value quantity).⁸ Hospital j maximizes profits by choosing price p_j :

$$(2) \quad \max_{p_j} \pi_j = p_j D_j(p) - C_j(D_j(p); Z_j, W_j)$$

where D_j is j 's demand, and C_j is j 's cost function.

The first-order-condition is:

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

⁸See Lakdawalla and Philipson (1999). For example, let NFP hospitals have utility functions $U = \pi + v(q)$. Expanding the first term, we get $pq - C(q) + v(q) = pq - \tilde{C}(q)$, hence NFPs look like FPs with lower costs.

This can be rewritten as:

$$(3) \quad p_j = MC_j - \frac{D_j}{\frac{\partial D_j}{\partial p_j}}.$$

We can express demand, D_j , as a function of the probability of going to firm j .

$$D_j = \sum_{t=1}^T N_t \bar{q}_t Pr_{(t \rightarrow j)}$$

where $Pr_{(t \rightarrow j)}$ is the probability that type t goes to firm j , N_t is the number of consumers of type t , and \bar{q}_t is the average quantity consumed by type t .

The demand derivative with respect to price is:

$$\frac{\partial D_j}{\partial p_j} = \sum_{t=1}^T N_t \bar{q}_t \frac{\partial Pr_{(t \rightarrow j)}}{\partial p_j}$$

Given the utility function in (1), a consumer of type t goes to firm j if $U_{tj} > U_{tj'}$ for $j \neq j'$. Since the error term in the utility function (ε_{tj}) is distributed Weibull, we can express the probability of going to a firm using the logistic equation:

$$Pr_{(t \rightarrow j)} = \frac{\exp(-\alpha p_j + a_{tj})}{\sum_{t'=1}^T \exp(-\alpha p_j + a_{t'j})}$$

From this we get:

$$\frac{\partial Pr_{(t \rightarrow j)}}{\partial p_j} = -\alpha Pr_{(t \rightarrow j)}(1 - Pr_{(t \rightarrow j)})$$

Thus using the explicit functional form, we can rewrite equation (3) as:

$$(4) \quad p_j = MC_j + \frac{1}{\alpha} \frac{\sum_{t=1}^T N_t \bar{q}_t Pr_{(t \rightarrow j)}}{\sum_{t=1}^T N_t \bar{q}_t Pr_{(t \rightarrow j)}(1 - Pr_{(t \rightarrow j)})}$$

We can further rewrite equation (3) as

$$(5) \quad p_j = MC_j + \frac{1}{\alpha} \frac{1}{\sum_{t=1}^T \frac{N_t \bar{q}_t Pr_{(t \rightarrow j)}}{\sum_{t=1}^T N_t \bar{q}_t Pr_{(t \rightarrow j)}}(1 - Pr_{(t \rightarrow j)})}$$

where $Pr_{(t \rightarrow j)}$ is just the share of consumers of type t who chose firm j . The denominator of (5) is our logit competition index, LOCI (Λ_j) for hospital j . That is:

$$(6) \quad \Lambda_j = \sum_{t=1}^T \frac{N_t \bar{q}_t Pr_{(t \rightarrow j)}}{\sum_{t=1}^T N_t \bar{q}_t Pr_{(t \rightarrow j)}}(1 - Pr_{(t \rightarrow j)})$$

LOCI (Λ_j) is a measure of how competitive firm j 's market is. The first term is the proportion of firm j 's demand that comes from consumers of type t . This captures how important segment type t is to firm j . The second term, $(1 - Pr_{(t \rightarrow j)})$ is the proportion of consumers of type t who did

not choose firm j . Thus, it represents firm j 's weakness in consumer segment t . LOCI is bounded between zero and one, therefore we call it a competition index rather than a concentration index because it is higher in less concentrated markets. A monopolist in all segments has $\Lambda = 0$ and Λ approaches 1 in the limit for a firm that is atomistic for all consumer types. We can substitute LOCI back into the pricing equation to get

$$(7) \quad p_j = MC_j + \frac{1}{\alpha} \frac{1}{\Lambda_j}$$

which implies that the inverse of LOCI is the price-cost markup, up to scale ($1/\alpha$). Note that LOCI can be calculated without estimating a model. Its calculation requires only data on market shares ($Pr_{(t \rightarrow j)}$), population (N_t) and average quantities (\bar{q}_t).

Recall that LOCI is the inverse of the last term in equation (3), i.e., $\Lambda_j = \frac{\partial D_j}{\partial p_j} / D_j$. Therefore with a few manipulations we can use LOCI to calculate elasticities. Combining equations (3) and (7) we get the following equation:

$$(8) \quad p_j - MC_j = -D_j \frac{\partial p_j}{\partial D_j} = \frac{1}{\alpha} \frac{1}{\Lambda}$$

If we take the reciprocal and multiply by price, we get the absolute value of the elasticity

$$(9) \quad |\eta| = \alpha \Lambda p_j = -\frac{\partial D_j}{\partial p_j} \frac{p_j}{D_j} = \frac{p_j}{p_j - MC_j}$$

Notice that the LOCI is almost a fully-specified demand system which is proportional to price-cost markup. LOCI is estimated using information on market shares only. To make it a full demand system we need to estimate the structural parameter α . When we assume a multinomial demand form we get a one parameter demand system which is easy and convenient to work with. However, it exhibits some undesirable properties.

Additive random utility models in which the errors are independent across consumers (like the multinomial logit) can generate implausible substitution patterns. For a standard logit model (with no types) the demand derivative with respect to own price is $-\alpha Pr_j(1 - Pr_j)$. Thus, the own-price demand derivative depends only on firm j 's choice probability. The cross-price effect on j 's demand of another firm k 's price is $\alpha Pr_k Pr_j$. This implies that two firms that have the same market shares will have the same own and cross-price effects. This carries up to the market level if consumers are identical. This problem is alleviated if consumers are not identical because then the price effects also depend on consumer specific factors, not only market shares and the price parameter.

Notice that in our model, the market shares are identical within consumer type ($Pr_{(t \rightarrow j)}$), but differ across types. Since LOCI is calculated by summing across all types the problem is mitigated.

We need to now derive LOCI for systems with more than one firm. The hospital industry, in particular, is characterized by multiple firms under common ownership. These are called hospital systems. In other industries, an analogy to hospital systems is that a single firm may own multiple brands or plants. We represent this using an ownership matrix Θ which is a J by J matrix of zeros and ones. An entry of 1 in the jk place indicates that firms j and k belong to the same system. Similarly, an entry of 0 in the jk place indicates that firms j and k do not belong to the same system. Given this set-up, we can now rewrite equation (3) using matrix notation as

$$(10) \quad p_j = MC_j - \left[\Theta \otimes \left[\frac{\partial D_j}{\partial p_j} \right] \right]^{-1} D_j$$

where \otimes indicates a Hadamard product.⁹ The derivative matrix with respect to demand D is given by:

$$(11) \quad \frac{\partial D}{\partial p} = \alpha \begin{bmatrix} -\sum N_t \bar{q}_t Pr_{t1}(1 - Pr_{t1}) & \sum N_t \bar{q}_t Pr_{t1} Pr_{t2} & \dots & \sum N_t \bar{q}_t Pr_{t1} Pr_{tJ} \\ & -\sum N_t \bar{q}_t Pr_{t2}(1 - Pr_{t2}) & \dots & \sum N_t \bar{q}_t Pr_{t2} Pr_{tJ} \\ & & & \vdots \\ & & & -\sum N_t \bar{q}_t Pr_{tJ}(1 - Pr_{tJ}) \end{bmatrix}$$

Rearranging, we get:

$$(12) \quad \frac{1}{\alpha} \frac{\partial D}{\partial p} = \begin{bmatrix} -\sum N_t \bar{q}_t Pr_{t1}(1 - Pr_{t1}) & \sum N_t \bar{q}_t Pr_{t1} Pr_{t2} & \dots & \sum N_t \bar{q}_t Pr_{t1} Pr_{tJ} \\ & -\sum N_t \bar{q}_t Pr_{t2}(1 - Pr_{t2}) & \dots & \sum N_t \bar{q}_t Pr_{t2} Pr_{tJ} \\ & & & \vdots \\ & & & -\sum N_t \bar{q}_t Pr_{tJ}(1 - Pr_{tJ}) \end{bmatrix}$$

The LOCI measure taking account of common ownership is thus:

$$\Lambda_j^{-1} = \left[\Theta \otimes \frac{1}{\alpha} \frac{\partial D_j}{\partial p_j} \right]^{-1}$$

This gives us the same pricing equation as (7), with LOCI calculated to take account of common ownership.

⁹Element by element multiplication.

3.1. Using LOCI to Approximate Merger Effects. In empirical studies of hospital markets we are usually interested in the effect of mergers. We can use the LOCI to approximate the effects of such mergers on hospital prices.

To do merger analysis we need an estimated demand system, an estimated cost function, and knowledge of the ownership matrix. Consider a market with 3 independent firms, and let firms 1 and 2 merge. The pre- and post-merger ownership matrices are:

$$\Theta^{pre} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \Theta^{post} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The pre-merger prices for the 3 firms are:

$$\begin{aligned} p_1^{pre} &= MC_1 - \frac{D_1}{\partial D_1 / \partial p_1} \\ p_2^{pre} &= MC_2 - \frac{D_2}{\partial D_2 / \partial p_2} \\ p_3^{pre} &= MC_3 - \frac{D_3}{\partial D_3 / \partial p_3} \end{aligned}$$

The post-merger pricing equations for the merging firms are:

$$\begin{aligned} p_1^{post} &= MC_1 - \frac{D_1}{\partial D_1 / \partial p_1} + (p_2^{post} - MC_2) \frac{\partial D_2 / \partial p_1}{\partial D_1 / \partial p_1} \\ p_2^{post} &= MC_2 - \frac{D_2}{\partial D_2 / \partial p_2} + (p_1^{post} - MC_1) \frac{\partial D_1 / \partial p_2}{\partial D_2 / \partial p_2} \end{aligned}$$

The pricing equation for the 3rd firm is the same, although the price of course will change.

We can solve these 3 equations for the post-merger prices. This will require solving them iteratively, since they are nonlinear equations. This is feasible, but can be time consuming. There is, however, an approximation we can use which is very simple to calculate. This can be used as a quick screen, or as a way of generating starting values for the exact merger simulation.¹⁰

Recall that the price-cost markup for an independent firm is:

$$p_j - MC_j = -\frac{D_j}{\partial D_j / \partial p_j}$$

¹⁰The approximation we use can be the first iteration solving for the true equilibrium. Thus this is a “first-order” method of approximation.

Substituting this expression for firm 2 into the pricing equation for firm 1 we get our approximation for firm 1's post-merger price:

$$(13) \quad p_1^{post} \approx MC_1 - \frac{D_1}{\partial D_1 / \partial p_1} - \left[\frac{D_2}{\partial D_2 / \partial p_2} \right] \frac{\partial D_2 / \partial p_1}{\partial D_1 / \partial p_1}$$

The expression for firm 2 is symmetric. We can thus calculate the approximate merger price effect as:

$$(14) \quad p_1^{post} - p_1^{pre} \approx \left[\frac{D_2}{\partial D_2 / \partial p_2} \right] \frac{\partial D_2 / \partial p_1}{\partial D_1 / \partial p_1}$$

Using the expressions for LOCI and the demand derivatives this becomes:

$$(15) \quad p_1^{post} - p_1^{pre} \approx \frac{1}{\alpha} \frac{1}{\Lambda_2} \frac{\alpha \sum N_t Pr_{(t \rightarrow 2)} Pr_{(t \rightarrow 1)}}{\alpha \sum N_t Pr_{(t \rightarrow 1)} (1 - Pr_{(t \rightarrow 1)})}$$

This simplifies to the final form:

$$(16) \quad p_1^{post} - p_1^{pre} \approx \frac{1}{\alpha} \frac{1}{\Lambda_2} \frac{\sum N_t Pr_{(t \rightarrow 2)} Pr_{(t \rightarrow 1)}}{\sum N_t Pr_{(t \rightarrow 1)} (1 - Pr_{(t \rightarrow 1)})}$$

From this it is clear that firm 1's approximate price increase is increasing in firm 2's markup ($\frac{1}{\Lambda_2}$). The price change is also increasing in the degree of overlap between the markets of firms 1 and 2, and decreasing in the slope of firm 1's demand.

Now consider the last term in equation (16). This is a measure of how responsive firm 2's demand is to 1's price, i.e., how substitutable they are. This is a measure of the extent to which firms 1 and 2 serve the same market, i.e., the extent of their overlap. We call this LOCI-Overlap:

$$(17) \quad \Lambda_{12} = \frac{\sum N_t Pr_{(t \rightarrow 2)} Pr_{(t \rightarrow 1)}}{\sum N_t Pr_{(t \rightarrow 1)} (1 - Pr_{(t \rightarrow 1)})}$$

This LOCI measure can also easily be calculated with minimal data and pencil and paper (or a spreadsheet). We can now re-express the approximate merger price increase as a function of LOCI-Overlap:

$$(18) \quad p_1^{post} - p_1^{pre} \approx \frac{1}{\alpha} \frac{\Lambda_{12}}{\Lambda_2}$$

Everything here can be obtained from simple calculation, except α . One may obtain α via estimation or calibration. If we don't want to estimate α we can calculate the price increase due to merger as a proportion of the pre-merger markup:

$$(19) \quad \begin{aligned} \frac{p_1^{post} - p_1^{pre}}{p_1^{pre} - MC_1} &\approx \left[\frac{1}{\alpha} \frac{\Lambda_{12}}{\Lambda_2} \right] \div \frac{1}{\alpha} \Lambda_1 \\ \frac{p_1^{post} - p_1^{pre}}{p_1^{pre} - MC_1} &\approx \frac{\Lambda_{12}}{\Lambda_2 \Lambda_1} \end{aligned}$$

This can be calculated very simply, and the approximate merger price increase can be recovered if there is some information on pre-merger markup.

The approximate merger price increases, while useful, are likely to be underestimates since it ignores firms' optimal reactions. It ignores the incentives of non-merging firms to raise price and the consequent effects on the pricing incentives of the merging parties. It also ignores feedback inside the merger — once firm 1 has increased its price, firm 2's incentive to raise price increases.

4. Econometric Specification

Our estimating equation is equation (7). Given calculated values of LOCI, equation (7) is linear in parameters so we can estimate it using least squares. We do not observe marginal cost, so we must assume something about the determinants of marginal cost. We assume constant returns to scale, so we only need use cost shifters to control for cost differences across hospitals (we intend to test the validity of this assumption). The cost shifters include a wage index, technology index, and an indicator for teaching status. Teaching hospitals are known to have higher costs than non-teaching hospitals (Sloan, Feldman and Steinwald, 1982). We also include dummy variables to capture effects of ownership type on prices, since the theory predicts NFP and public hospitals should set lower prices than FPs. Finally, since our data span four years we also include year dummies to control for secular trends over time. Consequently, we estimate the following equation:

$$(20) \quad p_{jt} = \beta_0 + \beta_1 C_{jt} + \beta_2 \frac{1}{LOCI_{jt}} + \zeta_t + \epsilon_{jt}$$

where t denotes time (years), j is an index for hospitals, C_{jt} represents all the cost shifters (wage index, technology index, teaching status, and ownership status), and the ζ_t represents year dummies.

4.1. Instrumenting Strategies. LOCI is likely endogenous, for the usual reasons. Market shares are not likely to be independent of unobserved factors that determine price.¹¹ An obvious approach is to instrument for LOCI. We can do this if we know something about demand. For instance, in the hospital industry distance traveled is important to patients. Patients tend to patronize hospitals that are close to their homes. Assuming that patient and hospital location are exogenous to hospital pricing, we can use patients' distances from hospitals as instruments. Specifically, we can run a logit of hospital choice on only distance. We can then calculate predicted shares from this estimation and use that to calculate a predicted LOCI. This predicted LOCI is a valid instrument for LOCI. We provide details on these calculations in section 5.6.2.

We also pursue another instrumenting strategy to examine the robustness of the results to the choice of instruments. Here we look for instruments that are likely to be correlated with market concentration and market power but unlikely to be correlated with unobserved hospital characteristics. For each firm, we use instruments that are correlated with the characteristics of other firms in its competitive environment. Thus, we use the following four instruments: the average wage at the closest hospital, average wage at the five closest hospitals, average distance to the closest hospital and the average distance to the five closest hospitals.

We report estimates using both instrumenting strategies in our results section.

5. Data

We use data from two main sources: the California Office of Statewide Health Planning and Development (OSHPD)¹² and the American Hospital Association (AHA). Three datasets maintained by OSHPD: the Annual Financial Data, annual discharge Data and the quarterly financial data and the annual survey of hospitals dataset collected by the AHA.

5.1. Annual Discharge Data. All hospitals are required to submit Patient Discharge Data semi-annually to the OSHPD. For every patient discharged from a hospital in California, data reported includes: patient demographic information, such as age, sex, zipcode, county of residence, and race; diagnostic information, ICD-9-CM diagnostic codes, DRG and MDC groupings; treatment information, ICD-9-CM procedure codes; external Cause of Injury codes (E-codes) and total charges with expected principal source of payment.

¹¹If we relax the assumption of constant returns, quantity will appear in the regression equation (20). This would also be endogenous.

¹²See www.oshpd.cahwnet.gov.

5.2. Annual Financial Data. In the state of California, all hospitals are required to submit a twenty-two page *Hospital Annual Disclosure Report* within four months of the end of the hospital's fiscal year. This report contains information about the type of ownership (Not-for-profit, For-profit or government), an inventory of services provide, number of beds and corresponding utilization patient statistics by payer; balance sheet and income statement; revenues by payer and revenue center; expenses by natural classification and cost centers and productive hours and average hourly rates by employee classification and cost center. From this dataset, we use information on ownership status, services provided, wages, type of care provided and teaching status.

5.3. Quarterly Financial Data. California law mandates all hospitals to submit quarterly reports within 45 days after the end of each calendar quarter. Submission is also required if the hospital had a change of license, closed or relocated to a new site during the quarter. This dataset contains information on aggregate deductions given by hospitals to insurance companies and HMOs. Data collected up to 1991 has information about total deductions given to all payers. From 1992 onwards, there is detailed information about deductions given to third party payers. We use this information on contractual deductions to calculate a fixed discount rate for each hospital.

5.4. American Hospital Association Data. The AHA collects data annually from every hospital in the United States. This dataset contains detailed information in hospital ownership. We link our sample hospitals to this dataset to get information on system membership.¹³

5.5. Sample Selection. For our LOCI calculation we use all discharges reported for each year except those with bad zipcode information.¹⁴ We use discharge information from patients whose payment came from HMO, PPO, other private, self-pay and Blue Cross Blue Shield. For all the years under consideration, about (50%) of the sample come from discharges with a public insurer (Medicare and Medi-Cal). We exclude these discharges because the price for hospital care for such patients is not determined by the market. Instead, hospitals are reimbursed on a fixed schedule based on the DRG of the patient. We include only those consumers with a diagnosis related group (DRG) with a frequency of at least 1,000. In addition, we restrict our sample to patients whose list price is between \$500 and \$500,000 or stayed at the hospital for at least one day (since we

¹³We actually use the modified AHA hospital system database used by Kessler and McClellan(2000). This database was extended by Chakravarty, Gaynor, Klepper and Vogt(2005). We supplemented this database with information reported on page zero of the Annual Financial Dataset provided to OSHPD by all hospitals and internet sources.

¹⁴Bad zipcode information corresponds with patients whose zipcode is unknown, are homeless or live outside the United States.

are interested in inpatient hospital care) but no more that 30 days. We restrict our sample to the described price range to eliminate price outliers since most moment based estimation methods such as OLS are sensitive to outliers. Hospitals that report less that 100 discharges in a given year are also excluded from the sample. We exclude patients who patronized Kaiser Permanente Hospitals since there is no price information. There are about 350,000 or about 10% of our discharges that fit this criteria. Ignoring such patients could introduce selection bias. Finally, we exclude all observations that have missing or useless information on any of the variables used in our analysis. See Table 1 for resulting sample after selections.

5.6. Calculated Variables. To estimate equation (7) we use a wage index, technology index, hospital ownership and teaching status to capture differences across hospitals in marginal cost. The wage index is a Paasche index calculated relative to the average hospital over nine job classifications. The technology index is the sum of dummy variables for the presence of 28 technology related services.¹⁵

5.6.1. Price and Quantity. Transactions prices are not reported as such in our data, nor are quantities. We use the methods employed by Gaynor and Vogt (2003) to extract price and quantity from the data. For each patient in our discharge data, we do not observe actual transaction prices. Instead, we observe list prices (called “charges” in the hospital industry). Most insurers pay a negotiated discount off list prices. However, we do not have information on the discount rate applied to each patient’s list price. There is information for each hospital on the total deductions granted and total revenues received from third party payers. We use this information to calculate a fixed discount rate for each hospital. We then multiply the discount rate by the observed total charges to get ”net charges” as shown below.

$$(21) \quad p_j q_i = \text{charges}_i \frac{GRI_j^{\text{oth3rd}} + GRO_j^{\text{oth3rd}} + DED_j^{\text{oth3rd}}}{GRI_j^{\text{oth3rd}} + GRO_j^{\text{oth3rd}}}$$

where GRI and GRO represent gross inpatient and gross outpatient revenues from “other third party” insurers respectively. The symbol DED represents contractual discounts from these revenues.

To determine price and quantity of inpatient hospital care demanded by each patient, we begin by writing the expenditure at hospital j for patient i :

$$(22) \quad \text{expenditure}_{ij} = p_j q_i$$

¹⁵These dummies are for services related to technologies like cardiac catheterization, echocardiology, ultrasonography etc. and are listed on page two of the Annual Financial dataset.

We assume that the patient's quantity consumed is a function of their characteristics, X_i ,¹⁶ and that the stochastic element ν_i is unobserved by both consumers and firms prior to hospitalization:

$$(23) \quad q_i = \exp(X_i\beta + \nu_i)$$

Then taking the natural logarithm on both side of equation (23) gives:

$$(24) \quad \ln(\text{expenditure}_{ij}) = \sum_j \chi_{i \rightarrow j}(\ln p_j) + X_i\beta + \nu_i$$

The term $\chi_{i \rightarrow j}$ is an indicator of whether consumer i goes to hospital j . The first term captures price at hospital j . The second term represents the average quantity consumed by individual i . Notice that, since hospital prices do not vary across patients, the first term in (24) may be captured by a set of hospital dummies. Thus a regression of complete set of hospital dummy variables and consumer characteristics gives prices for each hospital as well as the amount of hospital care consumed by a consumer.

5.6.2. Predicted LOCI. We use information on the latitudes and longitudes of zipcodes and hospitals to construct the distance from the centroid of each zipcode to each hospital (we have exact hospital location). We then estimate a logit for hospital choice using distance as the explanatory variable.¹⁷ We then calculate predicted probabilities of admission for every patient to all hospitals in our sample. We then construct our predicted LOCI using these predicted probabilities. By using predicted probabilities, we generate a LOCI based on exogenous characteristics of patients and hospitals.¹⁸

5.6.3. Herfindahl-Hirschman Index (HHI). For the purpose of comparison, we also calculate HHIs and estimate as SCP model for our sample. We calculate the HHI using two different methods. First, we calculate a hospital-specific HHI based on the method proposed by Zwanziger and Melnick (1988). We compute the HHI for each zip code based on patient origin,¹⁹ then for each hospital, we weight the zip code HHIs by the zip code's proportion of that hospital's total admissions. Finally we sum the weighted zip code HHIs for each hospital. We do this calculation using actual market

¹⁶The consumer characteristics used are as follows: 13 dummies for age category, 1 dummy for sex category, 5 dummies for race category, 305 dummies for Diagnosis Related Group (DRG), 3 dummies for severity, 3 dummies for type of admission and 24 variables for the number of other diagnoses

¹⁷The results of our conditional logit indicate that for every one mile increase in the distance from a patients zipcode to a hospital, the probability of patronizing that hospital decreases by about 15%. This estimate is consistent for all the years analyzed in this paper.

¹⁸Our approach is similar to the one used by Kessler and McClellan (2000).

¹⁹I.e., we calculate the market shares of all hospitals for patients who reside in the same zip code.

shares and predicted market shares as in Kessler and McClellan (2000). Our second geographic definition is health service area (HSA). An HSA is defined as one or more counties that are relatively self-contained with respect to routine hospital care. We calculate second HHI using HSA as the geographic market. This method corresponds more closely to most of the SCP literature, which uses HHIs based on geopolitical boundaries (e.g., county, MSA, etc.).

6. Descriptive Statistics

Descriptive statistics for the entire sample are reported in Table 2. Table 3 contains descriptive statistics by year. As Table 2 shows, the mean price for hospital services is \$4,889 with a standard deviation of 1,608. Price increases from 1992 (\$4,865) through 1994 (\$4,993), and then falls in 1995 (\$4,769). The average number of hospital beds for our period of analysis is about 190 with a standard deviation of 151. About 52% of the hospitals are not-for-profit hospitals, and for-profits form about 27% of our sample. About (20%) of our sample hospitals are teaching hospitals and the average distance between hospitals is about 6.5 miles. The average LOCI is 0.73, and it is steadily decreasing over time (0.74 in 1992 to 0.71 in 1995).

7. Results

7.1. LOCI. The results of our estimation using LOCI are summarized in Table 4. The first contains OLS estimates. The coefficient on inverse LOCI is 289 and significant at the 1% level. In our pricing specification, LOCI enters in inverse form, thus a positive coefficient on LOCI indicates that higher values of LOCI are associated with lower prices, as expected. The second column contains instrument variable estimates, where the instruments are average distance to the closest hospital, average distance to the five closest hospitals, the wage index at the closest hospital and the wage index at the five closest hospitals. The main results are contained in the last column of the table. In this specification, we instrument for LOCI using predicted LOCI. The point estimate is 528.74, significantly larger than we obtained using either OLS, or the other set of instruments. These results also show that wages increase prices and that teaching hospitals price on average \$728 above non-teaching hospitals. The technology index coefficient has the wrong sign and is not significant at conventional levels. Prices at for-profit hospitals are on average \$851 or 17% higher than at public hospitals. Not-for-profit hospitals do not set prices significantly different from public hospitals.

The parameter estimates for inverse LOCI from the regression are not directly interpretable in terms of effect of competition on prices. We therefore calculated the impact of discrete changes in

LOCI on price. We imagined a firm with the same market share in all market segments doubling its market share. This can be imagined as a “merger” of two firms with identical market shares in all market segments. For example, in a market with 5 firms with identical market shares, a merger between 2 of them will give the merged firm a market share of 40%. Since the effect of LOCI on price is nonlinear, we calculated this started at various base market shares. Table 5 contains these calculations, based on the IV estimates from the last column of Table 20. The increases in price are substantial (the antitrust authorities often use a 5% increase as a standard for judging whether a merger is anticompetitive), and increasing in the base market share.

Price increases every year from 1992 to 1994 but decreases in 1995. We run a separate regression using data from 1995 to check if 1995 is different from the other years. The regression results are summarized in Table 6. The results are consistent with the estimates from the panel regression discussed above. In 1995, the estimated effects of inverse LOCI are, however, quite a bit bigger than the panel regression estimates.

We also use LOCI to estimate demand elasticities for hospital care for the different regression specifications. These results are presented in Table 7. Hospitals in California faced an average demand elasticity of -3.55 between 1992 and 1995. The mean elasticity for for-profit and not-for-profit hospitals is -4.5 and -3.25 respectively. Public hospitals have a demand elasticity of -3.14 . This means public hospitals faced less elastic demand than hospitals of other ownership types. In 1995 the average demand elasticity facing hospitals is -3.46 . We also report the elasticities calculated by using the estimates from the 1995 only regression reported in Table 6. These elasticities are reported in the next to last column of the table. They are substantially larger than those estimated by using the full panel. For example, the average elasticity for the entire sample is -4.61 . For comparison purposes we report the estimates from the full structural model of Gaynor and Vogt (2003) in the last column labelled GV. As can be seen, the estimates obtained with LOCI are extremely close to those obtained from the structural model. The average elasticity from GV equals -4.85 , virtually indistinguishable from the estimate from the LOCI model.

7.2. HHI. Our estimates using HHI as the measure of market concentration is summarized in Table 8. The first column contains OLS estimates using the hospital-specific HHI. Since the HHI variable we used in the regression varies between 0 and 1 instead of the standard scale between 0 and 10,000, we must scale the point estimates down. The results indicate that if the hospital-specific HHI increases by 1,000 points, price should increase by \$195, or by less than 4%. In the

second column we estimate the same relation but use the hospital-specific HHI calculated using predicted probability as an instrument for HHI. The results from this estimation is unusual. The point estimate indicates a change in price of \$383 or 7.8% if the hospital-specific HHI increases by 1000 points. In both specifications, the HHI is significant at 1% significance level. Also, the wage index, teaching status and for-profit ownership have estimates with the right sign and are significant at conventional levels. When we define the geographic market to be the HSA, the estimates of the HHI parameter become noisy and insignificant.

8. Conclusion

In this paper, we develop a competition index for differentiated products oligopoly markets and apply it to California hospital markets. The estimates indicate that increases in the competition index decrease hospital prices. Increases in hospital market share (e.g., due to merger) are predicted to lead to significant price increases, which get larger the less competitive the market. We find that the price for hospital services in for-profit hospitals is highest. Also, government hospitals faced less elastic demand and consumers are most sensitive to increase in prices at for-profit hospitals. The results of our estimation are reasonably close to that of the fully specified structural demand model of Gaynor and Vogt(2003). Given that the LOCI(Λ) is theoretically grounded for differentiated products oligopoly markets, is easy to calculate, and does not require the definition of a geographical market, it could be used by the FTC and DOJ in their evaluation of mergers.

APPENDIX

A1. Herfindahl-Hirschman Index(HHI) and price cost margin. Consider an oligopoly that consists of n firms that produce a homogenous product. Each firm i chooses its output to maximize its profits so that

$$(25) \quad \pi_i = p(Q)q_i - mq_i,$$

where m is the constant marginal (and average variable) cost for each firm and p , the price, is a function of total industry output, $Q = nq_i$.

If the firms play Cournot then each firm's first-order condition is given by

$$\frac{\partial \pi_i}{\partial q_i} = \frac{\partial p(Q)}{\partial q_i} q_i + p(Q) - m = 0.$$

We can further rearrange to get:

$$MR = p(Q) + \frac{\partial p(Q)}{\partial q_i} q_i = m = MC.$$

We can rearrange the above equation in terms of the Lerner's index to get:

$$L \equiv \frac{p - m}{p} = -\frac{\partial p(Q) Q q_i}{\partial p(Q) Q} = -\frac{s_i}{\varepsilon} = -\frac{1}{n\varepsilon},$$

where $s_i \equiv \frac{q_i}{Q} = \frac{1}{n}$ is the output share of firm i and $\frac{1}{\varepsilon} = \frac{\partial p(Q)}{\partial q_i} \frac{Q}{P}$ is the reciprocal of the elasticity of demand. As pointed out in Cowling and Waterson (1976), the industry average of firms' price cost margins using shares is

$$\sum_i s_i \frac{p - m}{p} = -\frac{\sum s_i^2}{\varepsilon} \equiv -\frac{HHI}{\varepsilon}.$$

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TABLE 1. Sample Selection

Year	Total Discharges	Total hospitals	Total short term general hospitals	Total discharges after sample selection	Total hospitals after sample selection
1992	3,712,055	583	425	1,006,295	392
1993	3,664,629	567	417	980,084	386
1994	3,625,489	560	417	971,185	383
1995	3,629,322	553	407	929,093	374

TABLE 2. Summary statistics for all years

Variable	Mean	Std. Dev.	Min.	Max.
Price	4889	1608	1358	23192
Wage index	0.99388	0.15004	0.48433	4.10444
Wage index of closest hospital	0.99503	0.17084	0.56782	4.10444
Wage index of 5 closest hospitals	0.99590	0.09156	0.75998	1.81315
Distance to closest hospital	6.44712	10.18713	0.04425	84.28817
Distance to 5 closest hospitals	12.15383	14.35647	0.77891	111.51523
LOCI	0.72695	0.19458	0.20116	0.99961
LOCI(predicted)	0.76012	0.23618	0.01815	0.99983
Hospital specific HHI(predicted)	0.1998	0.21762	0.01535	0.95212
Hospital specific HHI	0.27263	0.12719	0.04838	0.81333
HSA HHI	0.12712	0.10379	0.03842	0.66697
Technology index	15.52117	6.05349	0	27
Beds	189.80912	150.64218	6	1418
For-Profit	0.27231	0.4453	0	1
Not-For-Profit	0.52117	0.49971	0	1
Government	0.20651	0.40494	0	1
Teaching status	0.19805	0.39866	0	1
N=1535				

TABLE 3. Summary Statistics by Year

Variable	1992	1993	1994	1995
Price	4864.828 (1388.133)	4926.417 (1609.203)	4992.815 (1782.733)	4768.836 (1631.694)
Wage index	0.975 (0.116)	1.000 (0.205)	1.002 (0.132)	0.998 (0.13)
Wage index of closest hospital	0.972 (0.113)	1.006 (0.257)	1.004 (0.138)	0.998 (0.134)
Wage index of 5 closest hospitals	0.977 (0.075)	1.001 (0.108)	1.006 (0.086)	1.001 (0.092)
Distance to closest hospital	6.509 (10.329)	6.518 (10.392)	6.390 (10.08)	6.368 (9.97)
Distance to 5 closest hospitals	12.238 (14.593)	12.253 (14.659)	12.173 (14.409)	11.943 (13.78)
LOCI	0.738 (0.192)	0.734 (0.193)	0.724 (0.196)	0.711 (0.197)
LOCI (predicted)	0.767 (0.24)	0.766 (0.239)	0.758 (0.233)	0.749 (0.233)
Hospital specific HHI (predicted)	0.196 (0.217)	0.200 (0.22)	0.201 (0.219)	0.203 (0.215)
Hospital specific HHI	0.297 (0.113)	0.159 (0.102)	0.311 (0.11)	0.326 (0.107)
HSA HHI	0.123 (0.104)	0.121 (0.102)	0.126 (0.1)	0.138 (0.109)
Technology index	17.584 (5.39)	14.689 (6.082)	14.742 (6.188)	15.016 (6.064)
Beds	187.923 (152.522)	191.42 (154.431)	190.094 (149.008)	189.832 (146.901)
For-Profit	0.268 (0.443)	0.272 (0.446)	0.274 (0.447)	0.275 (0.447)
Not-For-Profit	0.523 (0.5)	0.518 (0.5)	0.520 (0.5)	0.524 (0.5)
Government	0.209 (0.407)	0.210 (0.408)	0.206 (0.405)	0.201 (0.401)
Teaching status	0.189 (0.392)	0.194 (0.396)	0.198 (0.399)	0.211 (0.409)
	N=392	N=386	N=383	N=374

Notes: Standard deviations are in the parentheses.

TABLE 4. Regression Results, LOCI

Dependent Variable: Price			
Variable	(OLS)	(IV1)	(IV2)
Wage Index	1597.23* (696.82)	1655.15* (718.55)	1687.81* (728.56)
Teaching Status	645.12** (201.72)	698.32** (211.27)	728.32** (215.91)
Technology Index	-2.99 (14.11)	-1.58 (14.49)	-0.78 (14.44)
Not-for-Profit	-48.20 (166.08)	-40.83 (167.01)	-36.68 (167.97)
For Profit	713.15** (217.12)	801.28** (232.03)	850.97** (242.65)
inverse LOCI	288.98** (98.72)	442.28* (179.33)	528.74** (181.62)
1992	182.49* (87.29)	193.43* (86.77)	199.60* (87.36)
1993	183.80** (67.66)	194.66** (68.05)	200.79** (68.41)
1994	235.46** (68.29)	241.53** (67.84)	244.95** (68.52)
Intercept	2458.31** (746.20)	2099.27* (844.25)	1896.80* (841.73)
Instruments:			
Wage Index at closest hospital	N	Y	N
Wage index of 5 closest hospitals	N	Y	N
Distance to closest hospital	N	Y	N
Distance to 5 closest hospitals	N	Y	N
Predicted LOCI	N	N	Y
N=1535			

Notes: Standard errors are reported in parentheses.
Significance levels : † : 10% * : 5% ** : 1%

TABLE 5. Calculated Effects of LOCI on Price

Δ in Market Share	Δ Price	% Δ
20% \rightarrow 40%	\$220.31	4.51
25% \rightarrow 50%	\$352.50	7.21
33% \rightarrow 67%	\$793.11	16.22

TABLE 6. Regression Results, LOCI (1995)

Dependent Variable: Price			
Variable	(OLS)	(IV1)	(IV2)
Wage Index	2227.12** (632.35)	2456.82** (638.15)	2387.19** (632.89)
Teaching Status	766.83** (262.88)	923.62** (275.88)	876.10** (280.87)
Technology Index	-5.46 (16.56)	-2.42 (17.15)	-3.34 (16.91)
Not-for-Profit	-378.51† (229.02)	-362.97 (234.27)	-367.68 (232.55)
For Profit	284.61 (270.72)	541.50† (313.30)	463.63 (315.56)
inverse LOCI	446.59** (114.95)	885.05** (233.10)	752.15** (243.72)
Intercept	1884.55** (690.48)	809.69 (858.10)	1135.50 (856.93)
Instruments:			
Wage Index at closest hospital	N	Y	N
Wage index of 5 closest hospitals	N	Y	N
Distance to closest hospital	N	Y	N
Distance to 5 closest hospitals	N	Y	N
Predicted LOCI	N	N	Y
N=374			

Notes: Standard errors are reported in parentheses.
Significance levels : † : 10% * : 5% ** : 1%

TABLE 7. Average Elasticities

	1992	1993	1994	1995	1995 Only	GV
All Hospitals	-3.53	-3.58	-3.63	-3.46	-4.61	-4.85
For-Profit Hospitals	-4.75	-4.60	-4.55	-4.10	-5.46	-5.52
Not-For-Profit Hospitals	-3.29	-3.34	-3.29	-3.09	-4.11	-4.55
Government Hospitals	-2.97	-3.10	-3.26	-3.24	-4.31	-4.68

TABLE 8. Regression Results, HHI

Dependent Variable: Price				
Variable	(OLS)	(IV)	(OLS)	(OLS)
Wage Index	1488.55* (655.21)	1489.03* (666.58)	1717.71* (705.91)	1569.45* (676.26)
Teaching Status	603.96** (204.57)	660.72** (211.95)	634.02** (209.42)	579** (214.11)
Technology Index	0.51 (14.64)	6.45 (16.14)	5.65 (15.89)	-0.31 (15.41)
Not-for-Profit	-35.75 (165.25)	-10.47 (168.52)	39.78 (172.13)	-60.94 (167.84)
For Profit	764.92** (214.57)	974.1** (269.24)	803.99** (232.39)	655.29** (227.93)
Hospital specific HHI	1953.84** (642.00)	3829.63** (1505.45)		
Hospital specific HHI (predicted)			970.44** (378.82)	
HSA HHI				1296.40 (813.43)
1992	205.46* (84.52)	247.32** (85.99)	148.8† (89.63)	171.02** (86.80)
1993	493.25** (116.11)	810** (254.42)	172.35* (67.50)	188.33** (68.60)
1994	254.93** (65.80)	284.6** (67.62)	229.23** (68.33)	242.21** (67.92)
Intercept	2319.4** (703.84)	1536.32† (949.72)	2396.29** (755.17)	2756.21** (701.89)
Instruments: Predicted HHI	N	Y	N	N
N=1535				

Notes: Standard errors are reported in parentheses.

Significance levels : † : 10% * : 5% ** : 1%