A Competition Index for Differentiated Products Oligopoly with an Application to Hospital Markets*

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Abstract

Industrial organization economists have long been interested in the relationship between price, quantity, and market power. A workhorse in studying these relationships, and in antitrust analysis, has been the Herfindahl-Hirschmann Index (HHI). However, the HHI is not an appropriate measure of market power for differentiated products markets. We develop a simple to calculate, theoretically appropriate competition index for differentiated products oligopoly. Our index, which we term LOCI, is bounded between zero and one and increases with the competitiveness of a market. We apply our method to data on hospital markets and find that our index produces estimated demand elasticities that our no different from those calculated from a fully specified structural model of hospital behavior. Further, LOCI generates predictions of price effects for actual hospital mergers that are statistically indistinguishable from those generated from a structural model and from a retrospective study.

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1 Introduction

Industrial organization economists have long been interested in the relationship between price, quantity, and market power. A workhorse in studying these relationships, and in antitrust analysis, has been the Herfindahl-Hirschmann Index (HHI). The structure-conduct-performance (SCP) paradigm (developed by Bain, 1951) employs a measure of concentration, usually the HHI, as the key explanatory variable in a regression explaining price, price-cost margin, or profits. In antitrust the HHI has been extensively employed in merger analysis. The magnitude of the HHI is used by the federal antitrust authorities for indicating when horizontal mergers are likely to be problematic and receive scrutiny (Federal Trade Commission and Department of Justice, 1992), and the HHIs calculated by plaintiffs and defendants often play a large, and sometimes decisive, role in deciding antitrust suits.\footnote{Via the path of market definition (e.g. Baker, 2007; Areeda et al., 2007; Farrell and Shapiro, 2010; Kaplow, 2010).}

The use of the HHI has fallen into disfavor in academic studies. There is also increasing dissatisfaction with its use in antitrust. While there are a number of important criticisms of the SCP empirical approach (see, e.g., Bresnahan, 1989; Schmalensee, 1989), the one on which we focus here is its applicability to differentiated product markets. It is well known that the HHI and the commonly used SCP empirical regression specification can only be derived from a Cournot (homogeneous product) model (see, e.g., Cowling and Waterson, 1976; Tirole, 1988). As a consequence, the HHI isn’t theoretically justified in the case of differentiated product markets. This issue has increased in importance as differentiated products markets have become an increasingly larger part of the economy (e.g., most consumer products, health care, automobiles, etc.). In the case of antitrust, the HHI may not capture the true nature of competition among different brands. If some subset of brands in a market are particularly close substitutes, then the competition between these brands is the relevant antitrust concern, and a measure like the HHI that is market wide and (implicitly) treats all brands as equally close substitutes isn’t really appropriate and may mask the true nature of competition (Shapiro, 1996).

As the SCP approach has fallen into disfavor, structural econometric models have emerged as a replacement. This approach estimates demand, cost, and pricing equations based on a specific model of competitive conduct. The implied econometric models have the virtue of being derived from explicit economic models that capture the underlying structure of the economic system. Structural models are well suited for modeling differentiated products markets. They can capture the nature of substitution between brands, which is a key factor driving strategic interactions in these markets (Anderson et al., 1992; Berry, 1994; Berry et al., 1995, 2004). However, they are also usually very complicated and difficult to estimate. Thus, at one end of the the spectrum, we have the HHI, which is very easy to calculate once there are 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 tend to be complicated and difficult to estimate.

There have also been efforts by antitrust economists to develop simple measures of market power appropriate for differentiated products markets. The diversion ratio measures the
share of demand that is lost by one brand due to increasing its price that is captured by another brand. This captures the degree of substitutability between two brands, and thus how close competitors they are (Shapiro, 1996). While the diversion ratio is formally defined using cross and own elasticities, in practice it is often measured using consumer survey data or data on market shares (Shapiro, 1996). Farrell and Shapiro (2010) develop a measure of upward pricing pressure (UPP) as an easy to use tool appropriate for evaluating merger effects in differentiated products industries. UPP requires data on (pre-merger) prices and costs and on substitution (the diversion ratio). Werden (1996) proposes a test for whether a merger is welfare enhancing that can be calculated with only data on price-cost margins and diversion ratios, and does not depend on assumptions about functional form.

We contribute to this literature by developing a competition index that is theoretically justified for differentiated products oligopoly, which can be calculated and used in the same way as the HHI. Our index, which we term LOCI, for LOgit Competition Index, can be used on its own or to estimate an econometric model that is derived as the explicit reduced form pricing equation from a full structural model. LOCI simply depends on data on market shares and observable consumer types. It is bounded between zero and one. A firm with a monopoly for all consumer types has a value of LOCI that approaches 0 in the limit. A firm in a competitive market for all consumer types has a value of LOCI that approaches 1 in the limit.

To illustrate the use of this measure we apply our index to 1992 to 1995 hospital data from California. In our first empirical exercise, we estimate the relationship between inpatient hospital price and LOCI. Hospital care is a differentiated product, and hospital markets can be thought of as “natural” oligopolies (Gaynor and Town, 2012b). We then use our index to calculate demand elasticities and to simulate the price effects of hypothetical and consummated mergers. We validate the performance of our index by comparing our estimates with that of a fully specified structural model of hospital behavior proposed by Gaynor and Vogt (2003). Finally, we use our index to predict the price effects of two controversial mergers that happened in California in the 1990s.

Our empirical measure of LOCI has a mean of 0.727 for the entire sample, varying from a minimum of 0.201 to a maximum of 0.999. Recall that a low value of LOCI indicates less competition, and vice versa (1 equals perfect competition). The mean value of LOCI indicates that hospital markets in California look pretty competitive on average during this period. However, a number of markets are not very competitive (25 percent of markets have values of LOCI below 0.6), and the mean value of LOCI is declining over time, indicating that on average, markets were becoming less competitive.

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. In comparing calculated elasticities of LOCI with that of a fully specified structural model of hospital behavior, we estimate elasticities that are statistically identical to those from the Gaynor and Vogt (2003) model. LOCI estimates the average price elasticity demand for inpatient hospital care in 1995 to be -4.61. Government hospitals face a less elastic demand (-4.31) compared to for-profit (-5.46) and nonprofit hospitals (-4.11). This is in comparison to -4.85, -4.68, -5.52, and -4.55 respectively by Gaynor and Vogt (2003).

For the first merger, our model predicts a negligible price increase post-merger for the 1996
deal between Stanford University and the University of California, San Fransisco (UCSF) hospitals. This negligible price effect suggests limited scope for cost savings and exercise of market power. Consistent with this prediction, two years after the merger was consummated the two entities split because of huge financial losses. For the second merger, we predict a 30% price increase at Summit Medical Center and an 8% price increase at Alta Bates Medical Center following their 1998 merger. A retrospective study by the FTC on this deal using detailed data from the two hospitals and claims data from three large health insurers indicate that after the merger, inpatient hospital prices were about 29% to 72% higher at Summit than at comparable hospitals (Tenn, 2011). With limited data, our model predicts a price increase that is consistent with the retrospective analysis of the FTC, suggesting that our model could be useful for ex post merger evaluation.

This paper is organized as follows. In the next section, we review prior literature on competition in hospital markets and the impact of mergers on hospital price. In Section 3, we derive our competition index and outline our merger simulation methodology. We present our empirical strategy in Section 4 and describe our data in 5. In Section 6 we present the results of our parameter estimates, elasticity calculations, and merger predictions. Section 7 concludes and summarizes the main results of the paper.

2 Background on Hospital Markets

2.1 Competition and Antitrust in Hospital Markets

The United States (US) hospital industry experienced a large number of mergers, acquisitions, consolidation, and closures in the 1990s. There were about 1,199 mergers and acquisitions in the hospital industry between 1994 and 2005 with about 826 of these occurring between 1994 and 1999 (Irving Levin Associates, 2012). The merger wave affected all regions in the US with the South leading with the most consolidation (Vogt and Town, 2007). Consequently, this led to a dramatic increase in the level of concentration in local markets. The average resident of a metropolitan area lived in a moderately concentrated hospital market (with a Herfindahl-Hirschman Index (HHI)\(^2\) of 1,574) in 1990.\(^3\) In 2003, this average metropolitan resident lived in a market with hospital concentration index of 2,323, highly concentrated by US antitrust standards (Vogt and Town, 2007).

This wave of mergers did not go unchallenged. Hospital markets were an active area of antitrust enforcement in the 1990s. Federal and state antitrust authorities sought to block several hospital mergers.\(^4\) However, antitrust authorities lost seven consecutive merger challenges from 1994 onwards because the government could not convince the courts either of the relevant geographic market that supports their case (Farrell et al., 2009; Gaynor et al., 2011) or that nonprofit hospitals could exploit their market power and engage in anticompetitive activities (Philipson and Posner, 2009; Farrell et al., 2009). Following these

\(^2\)HHI is defined as the sum of squares of the market shares of the competitors in the market.

\(^3\)Antitrust enforcement agencies consider a market with HHI between 1,000 and 1,800 as moderately concentrated (Department of Justice and Federal Trade Commission, 1997).

losses, the Federal Trade Commission (FTC) launched the Hospital Merger Retrospectives Project in 2002 to get a better understanding of competition and merger effects in hospital markets through a critical analysis of consummated mergers (Farrell et al., 2009; Haas-Wilson and Garmon, 2011). These retrospective studies also provide a basis for comparing the predictive effect of proposed merger methods.

2.2 Effects of US Hospital Mergers on Price

There is extensive research on the price effects of US hospital mergers. A review of three decades of research on the effect of consolidation on price in hospital industry by Vogt and Town (2007) and Gaynor and Town (2012a) find that hospital mergers generally increase prices. This overall finding is true irrespective of the use of different methodologies (e.g. event study or simulation), different geographic regions (e.g. California, Florida, or all of the United States), different measures of price (e.g. charges, discounts from charges, or transaction price).

Evidence from event studies that use data before and after a merger to assess the impact of a merger on price find that relative to control hospitals that merging entities generally increase prices by 10% or more (Vita and Sacher, 2001; Dafny, 2009; Haas-Wilson and Garmon, 2011; Tenn, 2011; Thompson, 2011). This effect is larger when hospitals merge in concentrated markets. In such markets, most mergers trigger a price increase of at least 20%.

There are few merger simulation studies on US hospital markets. These studies also find large price increases post merger. Town and Vistnes (2001) find price increases often greater than 5% even in a relatively unconcentrated Los Angeles hospital market. Gaynor and Vogt (2003) find that change in market structure that would have resulted in one hospital system owning the three largest hospitals in a five hospital county would have resulted in price increases of more than 50%.

3 Deriving the Logit Competition Index (LOCI)

We consider a model with multinomial logit demand and observable consumer heterogeneity (e.g. Gaynor and Vogt, 2003; Berry et al., 2004). There are \( j = 1 \ldots J \) firms (hospitals) facing \( t = 1 \ldots T \) 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, types could be males aged 18 to 25 or couples with 2 or more children under age 7 earning over $100,000 per year. In the hospital industry, the key differentiating characteristic is distance. Consumers strongly prefer to seek care at hospitals that are close to them (Buchmueller et al., 2006; McGuirk et al., 1984; Dranove et al., 1993). In fact, Gaynor and Vogt (2003) find that the most important predictor of hospital demand is distance to a hospital. Thus, in our empirical application we use distance to a hospital as a dimension in our definition of types.

We assume demand is generated by a discrete choice problem in which each consumer chooses a brand and consumes one unit (this can include an outside good). Consumers of
type $t$ are assumed to have homogeneous preferences with respect to a given brand $j$. Given this characterization, the utility of consumers of type $t$ who choose brand $j$ is:

$$U_{tj} = -\alpha p_j + a_{tj} + \epsilon_{tj}$$  \hspace{1cm} (1)

where $p_j$ is the price of brand $j$. The error term $\epsilon_{tj}$ is distributed Weibull, so this utility generates a logit demand system. Unobservable characteristics are captured nonparametrically through $a_{tj}$. 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.

The firm owning brand $j$ maximizes profits by choosing price $p_j$:

$$\max_{p_j} \pi_j = p_j D_j(p) - C_j(D_j(p))$$  \hspace{1cm} (2)

where $D_j$ is $j$'s demand, $p$ is a vector of all brands' prices, and $C_j$ is $j$'s cost function. The first-order-condition is:

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

This can be rewritten as:

$$p_j = MC_j - \frac{D_j}{\partial p_j}$$  \hspace{1cm} (3)

Given the segmentation of consumers by type, we calculate the demand facing a brand as the sum across all types of the probability that consumers of type $t$ choose a brand multiplied by the total number of consumers of type $t$. Given consumer utility, the expected demand for brand $j$ is:

$$\hat{D}_j = \sum_{t=1}^{T} N_t \tilde{q}_t Pr \{ t \rightarrow j | p_j, \xi \}$$

where $Pr \{ t \rightarrow j | p_j, \xi \}$ is expressed as:

$$Pr \{ t \rightarrow j | p_j, \xi \} = \frac{\exp \{ U_{tj}(a_{tj}, \alpha, \epsilon_{tj}) \}}{\sum_{t'=1}^{T} \exp \{ U_{t'j}(a_{t'j}, \alpha, \epsilon_{t'j}) \}}$$

Similarly, the demand derivative is derived as:

$$\frac{\partial \hat{D}_j}{\partial p_j} = -\alpha \sum_{t=1}^{T} N_t \tilde{q}_t Pr \{ t \rightarrow j | p_j, \xi \} (1 - Pr \{ t \rightarrow j | p_j, \xi \})$$

\hspace{1cm} 5This may be a strong assumption, depending on the type and the brand. Some care is necessary in designating types in order to try to have the empirics conform to this assumption.

\hspace{1cm} 6Assuming, for the moment, that all brands are independently owned. We treat the case of brands owned in common in the next section.
Using the explicit functional form, equation (3) becomes

\[ p_j = MC_j + \frac{1}{\alpha} \frac{\sum_{t=1}^{T} N_{t}q_{t}Pr \{ t \rightarrow j|p_{j}, \xi \}}{\sum_{t=1}^{T} N_{t}q_{t}Pr \{ t \rightarrow j|p_{j}, \xi \} (1 - Pr \{ t \rightarrow j|p_{j}, \xi \})} \]

We can further rewrite equation (3) as

\[ p_j = MC_j + \frac{1}{\alpha} \frac{1}{\sum_{t=1}^{T} N_{t}q_{t}Pr \{ t \rightarrow j|p_{j}, \xi \} (1 - Pr \{ t \rightarrow j|p_{j}, \xi \})} \]

where \( Pr \{ t \rightarrow j|p_{j}, \xi \} \) is just the share of consumers of type \( t \) who chose brand \( j \). The denominator of equation (4) is our logit competition index, LOCI (\( \Lambda_j \)) for brand \( j \). That is:

\[ \Lambda_j = \sum_{t=1}^{T} \frac{N_{t}q_{t}Pr \{ t \rightarrow j|p_{j}, \xi \}}{\sum_{t=1}^{T} N_{t}q_{t}Pr \{ t \rightarrow j|p_{j}, \xi \} (1 - Pr \{ t \rightarrow j|p_{j}, \xi \})} \]

\( \Lambda_j \) is a measure of how competitive is brand \( j \)’s market. The first term is the proportion of brand \( j \)’s demand that comes from consumers of type \( t \). This captures how important segment type \( t \) is to brand \( j \). The second term, \( (1 - Pr \{ t \rightarrow j|p_{j}, \xi \}) \), is the proportion of consumers of type \( t \) who did not choose brand \( j \). Thus, it represents brand \( j \)’s weakness in consumer segment \( t \). \( \Lambda_j \) is bounded between 0 and 1, therefore we call it a competition index rather than a concentration index because it is higher in less concentrated markets. A brand with a monopoly in all types has \( \Lambda_j = 0 \); \( \Lambda_j \) approaches 1 in the limit for a brand that is atomistic for all consumer types.

We can substitute \( \Lambda_j \) back into the pricing equation to get

\[ p_j = MC_j + \frac{1}{\alpha} \frac{1}{\Lambda_j} \]

which implies that the inverse of LOCI is the price-cost markup, up to scale \((1/\alpha)\). Note that LOCI as expressed above can be calculated without estimating a model. Calculation requires only data on market shares \((1 - Pr \{ t \rightarrow j|p_{j}, \xi \})\), population, \( N_t \), and average quantities, \( q_t \).

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 since

\[ p_j - MC_j = -D_j \frac{\partial p_j}{\partial D_j} = \frac{1}{\alpha} \frac{1}{\Lambda_j} \]

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

\[ |\eta| = \alpha \Lambda p_j = - \frac{\partial D_j}{\partial p_j} \frac{p_j}{D_j} = \frac{p_j}{p_j - MC_j} \]

Notice that LOCI is almost a fully-specified demand system which is proportional to price-cost markup. To make it a full demand system we need to estimate the structural parameter
α. Estimating α gives us a one parameter demand system which is easy and convenient to work with, but has some restrictive 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 brand j’s choice probability. The cross-price effect on j’s demand of another brand k’s price is \(\alpha Pr_k Pr_j\). This implies that two brands with 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 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 \(Pr \{t \rightarrow j|p_j, \xi\}\), but differ across types. Since LOCI is calculated by summing across all types the problem is mitigated.

Once we have specified demand \(D_j\) we can calculate it with data. The estimate of \(\frac{\partial Pr \{t \rightarrow j|p_j, \xi\}}{\partial p_j}\) is calculated using market shares. The only component of the demand derivative that cannot be calculated using data is the parameter α. We outline how we estimate α in a subsequent section.

3.1 Common Ownership

We need to now derive LOCI for multiple brands owned by a single firm, which is a very common phenomenon. We represent this using an ownership matrix \(\Theta\) which is a \(J\) by \(J\) matrix of zeros and ones. An entry of 1 in the \(jk\) place indicates that brands \(j\) and \(k\) belong to the same firm. Similarly, an entry of 0 in the \(jk\) place indicates that brands \(j\) and \(k\) do not belong to the same firm. Given this set-up, we can now rewrite equation (3) using matrix notation as

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

(8)

where \(\otimes\) indicates a Hadamard product.\(^7\) The derivative matrix with respect to demand \(D\) is given by:

\[
\frac{\partial D}{\partial p} = \alpha \begin{bmatrix}
- \sum N_t \bar{q}_t Pr_{t1}(1 - Pr_{t1}) & \sum N_t \bar{q}_t Pr_{t1} Pr_{t2} & \cdots & \sum N_t \bar{q}_t Pr_{t1} Pr_{tJ} \\
- \sum N_t \bar{q}_t Pr_{t2}(1 - Pr_{t2}) & \cdots & \sum N_t \bar{q}_t Pr_{t2} Pr_{tJ} \\
& & \ddots & \vdots \\
& & & - \sum N_t \bar{q}_t Pr_{tJ}(1 - Pr_{tJ})
\end{bmatrix}
\]

(9)

\(^7\)Element by element multiplication.
Rearranging, we get:

\[
\frac{1}{\alpha} \frac{\partial D}{\partial p} = \begin{bmatrix}
- \sum N_t \bar{q}_t P_{rt1} (1 - P_{rt1}) & \sum N_t \bar{q}_t P_{rt1} P_{rt2} & \ldots & \sum N_t \bar{q}_t P_{rt1} P_{rtJ} \\
- \sum N_t \bar{q}_t P_{rt2} (1 - P_{rt2}) & \ldots & \sum N_t \bar{q}_t P_{rt2} P_{rtJ} \\
\vdots \\
- \sum N_t \bar{q}_t P_{rtJ} (1 - P_{rtJ})
\end{bmatrix}
\tag{10}
\]

The LOCI measure taking account of common ownership is thus:

\[\Lambda_j^{-1} = \left[ \Theta \otimes \frac{1}{\alpha} \frac{\partial D}{\partial p} \right]^{-1}\]

This will give us the same pricing equation as (6), with LOCI calculated to take account of common ownership.

### 3.2 Simulating Mergers

Let \( P \) and \( D \) be the \( J \)-vectors of price and demand observed in our data. In differentiated products Bertrand markets, both merging and non-merging firms have an incentive to increase price as a result of a merger. Since products are strategic complements and reaction functions are upward sloping, we allow both merging and non-merging firms to respond to a merger by changing price. Using the estimated model of demand, we calculate the matrix of demand derivatives at these prices and quantities. We approximate the merger effects by linearizing the demand system at the pre-merger prices. Thus the demand intercept can be calculated as:

\[D_0 = \hat{D} - \left( \frac{\partial D}{\partial P} \right) P\]

Let pre-merger marginal cost be denoted by \( MC_0 \). To simulate post-merger prices, we use pre-merger data and change the industry structure to reflect a merger. In our model, this means we need to change the ownership matrix \( \Theta \). Let subscript 0 denote pre-merger data and subscript 1 denote post-merger data. If a merger changes the ownership matrix from \( \Theta_0 \) to \( \Theta_1 \) then starting with equation (8) we get:

\[P_0 = MC_0 - \left\{ \Theta_0 \otimes \frac{\partial D}{\partial P} \right\}^{-1} D\]

this means that if we change the ownership matrix to reflect the change in market structure then

\[P_0 \neq MC_0 - \left\{ \Theta_1 \otimes \frac{\partial D}{\partial P} \right\}^{-1} D\]
We need to find the post-merger price $P_1$ that solves the preceding equation.

\[
P_1 = MC_0 - \left\{ \Theta_1 \otimes \frac{\partial D}{\partial P} \right\}^{-1} D
\]

Rearranging and solving for $P_1$ we get

\[
P_1 = \left( I + \left\{ \Theta_1 \otimes \frac{\partial D}{\partial P} \right\}^{-1} \frac{\partial D}{\partial P} \right) MC_0 \left\{ \Theta \otimes \frac{\partial D}{\partial P} \right\}^{-1} D_0
\]

To get post-merger price, we simulate the above equation to convergence.

It’s also possible to calculate approximate merger price effects very simply using LOCI. While these are not as accurate as simulating the exact effects, they can be calculated with only a few data elements and with pencil and paper or a spreadsheet. We derive and explain the LOCI merger approximations in the Appendix.

4 Empirical Application

Our estimating equation is equation (6). This is derived directly from the structural model laid out in Section 3. Given calculated values of LOCI, equation (6) is linear in parameters so it can be estimated simply using only ordinary least squares. We do not observe marginal cost, so we must assume something about the determinants of marginal cost. Here, we assume constant returns to scale, so we only need to use cost shifters to control for cost differences across hospitals. The cost shifters we use are: a wage index, a technology index, and an indicator for teaching status. We also include dummy variables to capture the effects of hospital ownership type (nonprofit, for-profit) on prices. Finally, since our data span several years we include year dummies to control for secular trends over time. Consequently, we estimate the following equation:

\[
P_j = \delta + \gamma \frac{\partial C}{\partial D}(W_j, T_j, Z_j, O_j) + \phi \frac{1}{A_j} + \rho Y_t + \epsilon_{jt}
\]

where $t$ denotes time (years), $j$ is an index for hospitals, $\frac{\partial C}{\partial D}$ is a function of the wage index ($W_j$), the technology index ($T_j$), teaching status($Z_j$), and ownership status ($O_j$), $\phi$ is the estimate of $\frac{1}{\alpha}$ and $Y_t$ represents time dummies. This bears a strong resemblance to an SCP regression specification where price is the dependent variable and a measure of concentration is the key independent variable. The key difference, of course, is that we use LOCI, which is explicitly derived from a model of differentiated product oligopoly.

\[\text{footnote}{This is due to the fact that the parameter for scale economies are not statistically significant in the Gaynor and Vogt (2003) model.}\]
4.1 Instrumenting Strategies

While equation (11) can be estimated with OLS, LOCI is likely endogenous for the usual reasons. Market shares are not independent of unobserved factors that determine price. An obvious approach is to instrument for LOCI. For imperfectly competitive markets such as hospital markets, valid instruments for demand can be variables that affect markup or marginal cost (Berry, 1994; Berry et al., 1995) so 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 (Berry, 1994; Berry et al., 1995). The instruments are: the average wage at the closest hospital, the average wage at the five closest hospitals, the average distance to the closest hospital and the average distance to the five closest hospitals. We also use predicted market shares to calculate LOCI to address the endogeneity problem.

5 Data

We use three datasets maintained by the California Office of Statewide Health Planning and Development (OSHPD) and data from the California Hospital Data project. Our data are from 1992 to 1998. We get information from the Annual Discharge dataset on 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, and total charges with expected principal source of payment. Our data on hospital characteristics such as ownership status, services provided, wages, type of care provided and teaching status come from the Annual Financial Data. Last, the Quarterly Financial Data provide us with information on contractual deductions to calculate a fixed discount rate for each hospital. Data on hospital ownership is from the California Hospital Data project, internet sources, information reported on page zero of the Annual Financial Data as well as Hospital Changes and Hospital History files, all maintained by OSHPD.

5.1 Sample Selection

We use the same sample selection criteria as Gaynor and Vogt (2003). We use discharge information from patients whose payments came from HMO, PPO, other private, self-pay and Blue Cross Blue Shield. 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 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

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9If we relax the assumption of constant returns, quantity will appear in the regression equation. This would also be endogenous.
10See section 5.2.3 for an exposition on how we predict market shares.
11We exclude Medicare and MediCal because those entities set regulated prices for hospitals.
than 100 discharges in a given year are also excluded from the sample. We also exclude patients who patronized Kaiser Permanente Hospitals since there is no price information. Finally, we exclude all observations that have missing or unusable information on any of the variables used in our analysis. This leaves us with 1,535 observations on about 380 hospitals per year (the number of hospitals varies by year, see Table 2).

5.2 Calculated Variables

To estimate equation (11) 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.\textsuperscript{12} Hospital ownership are dummy variables indicating if the hospital is nonprofit, for-profit, or public. Teaching status is a dummy variable for if the hospital is a teaching hospital.

5.2.1 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.

\[
p_jq_i = \frac{GRI_{j}^{oth3rd} + GRO_{j}^{oth3rd} + DED_{j}^{oth3rd}}{GRI_{j}^{oth3rd} + GRO_{j}^{oth3rd}} \text{charges}_i \tag{12}
\]

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 \(i\):

\[
expenditure_{ij} = p_jq_i \tag{13}
\]

We assume that the patient’s quantity consumed is a function of their characteristics, \(X_i\),\textsuperscript{13} and that the stochastic element \(\nu_i\) is unobserved by both consumers and firms prior to

\textsuperscript{12}These dummies are for services related to technologies like cardiac catheterization, echocardiology, ultrasonography etc. and are listed on page two of the Annual Financial Data.

\textsuperscript{13}The 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.
hospitalization:

\[ q_i = \exp(X_i\beta + \nu_i) \]  

(14)

Then taking the natural logarithm on both side of equation (14) gives:

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

(15)

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 (15) may be captured by a set of hospital dummies. Thus a regression with a 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.

5.2.2 LOCI

Recall that equation (5) gives the formula for calculating LOCI. Calculating LOCI empirically is straightforward. All the components of LOCI can be calculated directly from data. The probability that patients of type \( t \) go to hospital \( j \), \( (1 - Pr\{t \rightarrow j | p_j, \xi\}) \), is calculated from data on market shares. \( N_t \) is the total number of patients of type \( t \) and \( t \) and \( q_t \) is the average quantity of inpatient care consumed by patients of type \( t \).

5.2.3 Predicted LOCI

We use information on the latitudes and longitudes of zip codes and hospitals to construct the distance from the centroid of each zip code to each hospital address. We then estimate a logit for hospital choice using distance as the explanatory variable.\(^\text{14}\) We 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.\(^\text{15}\)

6 Results

6.1 Descriptive Statistics

Tables 1 and 2 present descriptive statistics for the entire period and by year respectively. As Table 1 shows, the mean price for inpatient hospital services for the 1992 to 1995 period was $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 nonprofit hospitals, and for-profits form about 27% of our sample. About (20%) of our

\(^{14}\)The results of our conditional logit model indicate that for every one mile increase in the distance from a patients zip code 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.

\(^{15}\)Our approach is similar to the one used by Kessler and McClellan (2000).
sample hospitals are teaching hospitals and the average distance between hospitals is about 6.5 miles. Consistent with increasing consolidation in the California hospital market in the 1990s the average LOCI is 0.73, and it is steadily decreasing over time (0.74 in 1992 to 0.71 in 1995). The proportion of hospitals by ownership type remains stable over our sample period.

### 6.2 LOCI

The results of our estimation using LOCI are summarized in Table 3. Each column in the table represents a separate regression. The first column presents OLS estimates of the effect of inpatient hospital price on hospital characteristics, cost and LOCI. 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 instrumental 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. Our preferred specification is model 3, which is also an instrumental variables regression. This specification instruments for LOCI with predicted LOCI, as described above in Section 5.2.3. The point estimate of 528.74 is significantly larger than those obtained from models 1 and 2. These results also show that higher wages are associated with higher prices. In addition, 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 or nonprofit hospitals. Inpatient hospital prices at nonprofit hospitals are not statistically different from public hospitals. The technology index coefficient is very imprecisely estimated.

The parameter estimates for inverse LOCI from these regressions are not directly interpretable in terms of effect of competition on prices. We therefore calculate the impact of discrete changes in LOCI on price. We do these calculations for a hospital (brand, in the general application) with the same market share in all market segments doubling its market share. This can be imagined as a “merger” of two hospitals with identical market shares in all market segments. For example, in a market with 5 hospitals with identical market shares, a merger between 2 of them will give the merged entity a market share of 40%. Since the effect of LOCI on price is nonlinear, we calculate this starting at various base market shares. Table 4 contains these calculations, based on model 3, our preferred specification from Table 3. The increases in price are substantial (antitrust authorities often use a 5% increase as a standard for judging whether a merger is anticompetitive), and increasing in the base market share.

### 6.3 Demand Elasticities

We next use equation (7) to calculate the demand elasticity of inpatient hospital care to compare with estimates presented in Gaynor and Vogt (2003). To do this we first apply our empirical model to 1995 data only. We then use the estimated LOCI parameters shown in table A.1 in the Appendix to calculate the implied elasticities. In table 5, we present
the estimates of two models side-by-side for comparison. In general, demand for inpatient hospital care in 1995 is inelastic (-4.61). Consumers are most sensitive to price changes at for-profit hospitals (-5.46) and least sensitive to price changes at nonprofit hospitals (-4.11). Overall, the elasticity estimates of the models are very close, although the elasticity estimates from the LOCI model are somewhat smaller in absolute value.

6.4 Merger Simulation Results

6.4.1 Tenet Healthcare merger with OrNda Healthcorp, 1997

We first test how good our index is at simulating the price effects of mergers by analyzing the 1997 merger between Tenet Healthcare and OrNda Healthcorp reported in Gaynor and Vogt (2003) for comparison. The two firms owned several hospitals in overlapping markets; however, the only overlapping market that caused antitrust concern was San Luis Obispo county. There were five hospitals in San Luis Obispo county in 1997, of which Tenet and OrNda owned the largest three. The FTC allowed the merger to proceed with the stipulation that the merged entity divest French hospital. As in Gaynor and Vogt (2003) we use 1995 data to simulate the effect of this merger.

Table 6 presents the predicted price increases with and without the divestiture of French Hospital. The last two columns present the post-merger prices predicted by the LOCI and by the Gaynor and Vogt (2003) models, respectively. The estimates from the two models are quite close. For French hospital, Gaynor and Vogt (2003) predict a price increase of about 53%, while the LOCI model predicts a price increase of about 45%. For Sierra Vista Regional Medical Center, the point estimates of the two models differ by $1. In fact, for all the predictions except for General Hospital, where there is a $137 difference between the two models, the estimates of Gaynor and Vogt (2003) are contained in a 95% confidence interval of the LOCI predictions. A comparison of the two models in the case of divestiture also highlights the similarity of the two models.

Since the main source of identification of the Gaynor and Vogt (2003) model is distance, it is not surprising that the two models produce similar predictions. In general, the LOCI model performs well with respect to the Gaynor and Vogt (2003) model even though it makes strong assumptions about consumer preferences.

6.4.2 Stanford Healthcare and University of California, San Francisco, 1997

One of the most prominent mergers in California in the 1990s was the 1997 merger between Stanford University Health and the University of California Medical Center, San Francisco (UCSF). This merger was controversial from the start because Stanford Health is a private institution while UCSF is public. A merger between the two entities meant the transfer of public assets to an independent non-profit entity, UCSF Stanford Healthcare. The two organizations argued that a merger would cut costs, improve access to health care in the community and build a strong medical school to compete for scarce research grants. Though, the merger involved two large hospital systems, the FTC and DOJ did not challenge this merger. The merging entities are about 40 miles apart.

The merged entity began operations on July 1, 1997. In November 1997, UCSF Stanford Healthcare was formed as a private, nonprofit corporation combining Stanford Medical
Center, Lucille Salter Packard Children’s Hospital, UC San Francisco Medical Center and UC San Francisco’s Mount Zion Hospital.

We present estimates of the impact of this merger on prices in Table 7. We find a negligible impact of the merger on prices.\textsuperscript{16} The biggest price increase is a 1% increase at Mount Zion Medical Center. Given the substantial distance between the two entities, they were apparently not close competitors, so the merger had essentially no effect on prices.

Less than two years after this merger was consummated, the merger was dissolved due to huge financial losses. In March 2000, when the merger was officially dissolved, UCSF Stanford Healthcare had lost about $176 million. This steep loss was in sharp contrast to the performance of the two entities pre-merger. According to Kastor (2001) in the fiscal year prior to the merger, UCSF and Stanford Healthcare made $27 million and $9 million in profit respectively. While the financial losses might have occurred even if the merger had enhanced pricing power for the merged firm, clearly there was no increase in market power that might have generated revenues to offset these costs (not that a merger that generated both higher costs and higher prices would be socially desirable).

6.4.3 Alta Bates Medical Center and Summit Medical Merger, 1999

The proposed merger between Alta Bates Medical Center (Alta Bates) and Summit Medical Center (Summit) was the most litigated hospital merger case in California in the 1990s. In early January, 1999, Sutter Health, a Sacramento-based nonprofit hospital system, notified the appropriate entities of their intention to acquire Oakland-based Summit Medical Center. The 2.5 mile distance between the two hospitals made Summit the closest rival of Alta Bates.\textsuperscript{17}

After a five-month investigation, FTC indicated that it would not block the merger on anticompetitive grounds. A month after the decision by the FTC, citing anti-competitive concerns, the California Attorney General filed a suit in federal court to block the merger. The federal courts denied the state attorney’s injunction. Shortly after the ruling, the merger was consummated. The state appealed the ruling but lost the appeal as well.

Our LOCI model simulation predicts that this merger would increase price by about 8% at Alta Bates Medical Center and by 31% at Summit Medical Center. The model predicts negligible price increases at the other acute general hospitals owned by Sutter. The highest price increase in the Sutter network other than the two merging hospitals is a 5% price increase at Eden Medical Center.

As Table 8 shows, pre-merger prices at Summit and Alta Bates were $3,893 and $5,238 respectively. After the merger, prices at the two hospitals were very similar ($5,099 vs. $5,646). Our simulation shows that the merger increased price at Summit Medical Center by a substantial amount, and should have raised anticompetitive concerns.

\textsuperscript{16}We do not show prices at Lucille Salter Packard Children’s Hospital since it is a children’s hospital and not a short-term general hospital.

\textsuperscript{17}Alameda County Medical Center is the closest hospital to Summit Medical Center. However, Alameda County Medical Center serves a disproportional number of public-paying and indigent patients making it less of a competitor. Kaiser Permanente also has a hospital in Oakland but that cannot be considered a direct competitor since Kaiser is an integrated HMO that serves patients with Kaiser health plans. Also, Kaiser does not report price information to OSHPD, consequently, all Kaiser hospitals are excluded from our analysis.
The FTC subsequently did a retrospective analysis of this merger. Using data from Summit, Alta Bates, and data on actual amounts paid to these hospitals for inpatient admissions by three large health insurers, Tenn (2011) finds that, depending on the health insurer, the post-merger price change at Summit Medical Center was between 23% and 50% higher than the average price for similar hospitals. The post-merger price change at Alta Bates Medical Center is not statistically different from average price change of comparable hospitals. Our simulated price change of 30% price increase at Summit falls in the 23% to 50% range estimated by Tenn (2011). In addition, Tenn (2011)’s finding of negligible price increase at Alta Bates is consistent with our simulation results since the 95% confident interval of our estimate suggests a 4% to 12% price increase at Alta Bates.

7 Summary and Conclusion

We develop a simple competition index for differentiated product oligopoly markets and illustrate its use by applying it to the hospital market in California. Our index is simple to calculate like the HHI, but unlike the HHI, is grounded in economic theory like a fully specified structural model. However, LOCI does not require the estimation of a full-blown structural model. Our model makes restrictive assumptions about consumer preferences in order to estimate demand parameters. Overall we find that comparing predictions of mergers simulated with the LOCI model embodying these assumptions to a full structural model which employs standard, less restrictive, assumptions on preferences generates estimates that are very close to each other.

We use our index to estimate the impact of market concentration on price. 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. Calculated elasticities and merger effects estimated by our model are statistically identical to estimates from the fully specified structural model of hospital behavior proposed by Gaynor and Vogt (2003). In addition, the predicted merger effects of a consummated merger in California are consistent with estimates from a retrospective analysis conducted by the FTC.

LOCI is a simple, easy to use competition index grounded in economic theory that can be used in a straightforward way as an indicator of market power, for example for ex ante horizontal merger diagnostics with differentiated products firms. It helps to bridge the gap between older, easy to use approaches that are not well grounded in economics with newer approaches, that, while well grounded, can be time consuming and difficult to use. Economists have been engaging for some time now in important efforts to update the IO and antitrust toolkit with theoretically appropriate tools for differentiated product oligopolies. LOCI represents another element in that toolkit, which will hopefully increase our understanding of and approaches toward competition in the differentiated products markets which comprise such an important part of our economy.
References


Table 1: Summary Statistics for all Years

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<thead>
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<th>Variable</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price($)</td>
<td>4.889</td>
<td>1.608</td>
<td>1.358</td>
<td>23.192</td>
</tr>
<tr>
<td>Wage index</td>
<td>0.994</td>
<td>0.150</td>
<td>0.484</td>
<td>4.104</td>
</tr>
<tr>
<td>Wage index of closest hospital</td>
<td>0.995</td>
<td>0.171</td>
<td>0.568</td>
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<td>Wage index of 5 closest hospitals</td>
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<td>0.092</td>
<td>0.760</td>
<td>1.813</td>
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<td>Distance to closest hospital</td>
<td>6.447</td>
<td>10.187</td>
<td>0.044</td>
<td>84.288</td>
</tr>
<tr>
<td>Distance to 5 closest hospitals</td>
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<td>14.356</td>
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<td>111.515</td>
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<td>LOCI</td>
<td>0.727</td>
<td>0.194</td>
<td>0.201</td>
<td>0.999</td>
</tr>
<tr>
<td>LOCI(predicted)</td>
<td>0.760</td>
<td>0.236</td>
<td>0.018</td>
<td>0.999</td>
</tr>
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<td>Technology index</td>
<td>15.521</td>
<td>6.053</td>
<td>0</td>
<td>27</td>
</tr>
<tr>
<td>Beds</td>
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<td>6</td>
<td>1418</td>
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<td>0.445</td>
<td>0</td>
<td>1</td>
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<tr>
<td>Nonprofit</td>
<td>0.521</td>
<td>0.500</td>
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<td>1</td>
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<td>Government</td>
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<td>0</td>
<td>1</td>
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<tr>
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<td>0.198</td>
<td>0.399</td>
<td>0</td>
<td>1</td>
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N=1535  

Data Source: California Office of Statewide Health and Development (OSHPD). Notes: Author’s calculations, data is for years 1992 to 1995.
Table 2: Summary statistics by Year

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<td>Mean</td>
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<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
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<td>4992.815</td>
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<td>4768.836</td>
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<td>Beds</td>
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<td>191.42</td>
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<td>149.008</td>
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<td>0.998</td>
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<td>1.006</td>
<td>0.257</td>
<td>1.004</td>
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<td>Wage index of 5 closest hospitals</td>
<td>0.977</td>
<td>0.075</td>
<td>1.001</td>
<td>0.108</td>
<td>1.006</td>
<td>0.086</td>
<td>1.001</td>
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<td>0.734</td>
<td>0.193</td>
<td>0.724</td>
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<td>LOCI (pred)</td>
<td>0.767</td>
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<td>0.766</td>
<td>0.239</td>
<td>0.758</td>
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<td>Technology index</td>
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<td>14.689</td>
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<td>14.742</td>
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<td>15.016</td>
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<td>For-Profit</td>
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<td>0.443</td>
<td>0.272</td>
<td>0.446</td>
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N=392 N=386 N=383 N=374

Data Source: California Office of Statewide Health and Development (OSHPD). Notes: Author’s calculations, data is for years 1992 to 1995.
Table 3: Regression Results

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<th>Dependent Variable: Price</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
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<td>Wage Index</td>
<td>1597.23***</td>
<td>1655.15**</td>
<td>1687.81**</td>
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<td>(696.82)</td>
<td>(718.55)</td>
<td>(728.56)</td>
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<td>Teaching Status</td>
<td>645.12***</td>
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<td>728.32***</td>
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<td>(201.72)</td>
<td>(211.27)</td>
<td>(215.91)</td>
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<tr>
<td>Technology Index</td>
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<td>-1.58</td>
<td>-0.78</td>
</tr>
<tr>
<td></td>
<td>(14.11)</td>
<td>(14.49)</td>
<td>(14.44)</td>
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<td>Nonprofit</td>
<td>-48.20</td>
<td>-40.83</td>
<td>-36.68</td>
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<td>(166.08)</td>
<td>(167.01)</td>
<td>(167.97)</td>
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<td>For Profit</td>
<td>713.15***</td>
<td>801.28***</td>
<td>850.97***</td>
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<tr>
<td></td>
<td>(217.12)</td>
<td>(232.03)</td>
<td>(242.65)</td>
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<tr>
<td>Inverse LOCI</td>
<td>288.98***</td>
<td>442.28**</td>
<td>528.74***</td>
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<tr>
<td></td>
<td>(98.72)</td>
<td>(179.33)</td>
<td>(181.62)</td>
</tr>
<tr>
<td>1992</td>
<td>182.49**</td>
<td>193.43**</td>
<td>199.60**</td>
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<tr>
<td></td>
<td>(87.29)</td>
<td>(86.77)</td>
<td>(87.36)</td>
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<td>1993</td>
<td>183.80***</td>
<td>194.66***</td>
<td>200.79***</td>
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<td></td>
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<td>(67.84)</td>
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<tr>
<td>Intercept</td>
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<td>2099.27**</td>
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<td>(746.20)</td>
<td>(844.25)</td>
<td>(841.73)</td>
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*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

Data Source: California Office of Statewide Health and Development (OSHPD) for years 1992 to 1995. Standard errors are reported in parentheses. Omitted variables are government hospitals, and year 1995. Significance levels: * 10%, ** 5%, *** 1%
Table 4: Calculated Effects of LOCI on Price

<table>
<thead>
<tr>
<th>Δ in Market Share</th>
<th>Δ Price</th>
<th>%Δ</th>
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</thead>
<tbody>
<tr>
<td>20% → 40%</td>
<td>$220.31</td>
<td>4.51</td>
</tr>
<tr>
<td>25% → 50%</td>
<td>$352.50</td>
<td>7.21</td>
</tr>
<tr>
<td>33% → 67%</td>
<td>$793.11</td>
<td>16.22</td>
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Table 5: Average Elasticities

<table>
<thead>
<tr>
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<th>LOCI</th>
<th>GV(2003)</th>
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</thead>
<tbody>
<tr>
<td>All Hospitals</td>
<td>-4.61</td>
<td>-4.85</td>
</tr>
<tr>
<td></td>
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<td>(2.03)</td>
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<td>For-Profit Hospitals</td>
<td>-5.46</td>
<td>-5.52</td>
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<td></td>
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<td>(2.07)</td>
</tr>
<tr>
<td>Nonprofit Hospitals</td>
<td>-4.11</td>
<td>-4.55</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.74)</td>
</tr>
<tr>
<td>Government Hospitals</td>
<td>-4.31</td>
<td>-4.68</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.43)</td>
</tr>
</tbody>
</table>

Data Source: 1995 data from California Office of Statewide Health and Development (OSHPD). We calculate these elasticities with equation (7). Standard deviations are reported in parenthesis.
Table 6: Merger Simulation of the 1997 Tenet and Ornda merger

### San Luis Obispo County without Divestiture

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Premerger Owner</th>
<th>Postmerger Owner</th>
<th>Premerger Price</th>
<th>LOCI</th>
<th>GV (2003)</th>
</tr>
</thead>
<tbody>
<tr>
<td>French Hospital</td>
<td>Ornda</td>
<td>Tenet</td>
<td>$4,434</td>
<td>$6,409</td>
<td>$6,784</td>
</tr>
<tr>
<td>General</td>
<td>County</td>
<td>County</td>
<td>$4,577</td>
<td>$4,647</td>
<td>$4,784</td>
</tr>
<tr>
<td>Sierra Vista</td>
<td>Tenet</td>
<td>Tenet</td>
<td>$4,134</td>
<td>$5,468</td>
<td>$5,469</td>
</tr>
<tr>
<td>Arroyo Grande</td>
<td>Vista</td>
<td>Vista</td>
<td>$3,477</td>
<td>$3,693</td>
<td>$3,654</td>
</tr>
<tr>
<td>Twin Cities</td>
<td>Tenet</td>
<td>Tenet</td>
<td>$4,216</td>
<td>$5,356</td>
<td>$5,587</td>
</tr>
<tr>
<td>Marian Medical Center</td>
<td>Catholic</td>
<td>Catholic</td>
<td>$3,289</td>
<td>$3,370</td>
<td>$3,331</td>
</tr>
<tr>
<td>Valley Community</td>
<td>Ornda</td>
<td>Tenet</td>
<td>$4,439</td>
<td>$4,666</td>
<td>$4,552</td>
</tr>
</tbody>
</table>

### San Luis Obispo County with Divestiture

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Premerger Owner</th>
<th>Postmerger Owner</th>
<th>Premerger Price</th>
<th>LOCI</th>
<th>GV (2003)</th>
</tr>
</thead>
<tbody>
<tr>
<td>French Hospital</td>
<td>Ornda</td>
<td>Vista</td>
<td>$4,434</td>
<td>$4,518</td>
<td>$4,467</td>
</tr>
<tr>
<td>General</td>
<td>County</td>
<td>County</td>
<td>$4,577</td>
<td>$4,585</td>
<td>$4,607</td>
</tr>
<tr>
<td>Sierra Vista</td>
<td>Tenet</td>
<td>Tenet</td>
<td>$4,134</td>
<td>$4,312</td>
<td>$4,202</td>
</tr>
<tr>
<td>Arroyo Grande</td>
<td>Vista</td>
<td>Vista</td>
<td>$3,477</td>
<td>$4,042</td>
<td>$3,712</td>
</tr>
<tr>
<td>Twin Cities</td>
<td>Tenet</td>
<td>Tenet</td>
<td>$4,216</td>
<td>$4,330</td>
<td>$4,261</td>
</tr>
<tr>
<td>Marian Medical Center</td>
<td>Catholic</td>
<td>Catholic</td>
<td>$3,289</td>
<td>$3,343</td>
<td>$3,319</td>
</tr>
<tr>
<td>Valley Community</td>
<td>Ornda</td>
<td>Tenet</td>
<td>$4,439</td>
<td>$4,606</td>
<td>$4,512</td>
</tr>
</tbody>
</table>

Data Source: California Office of Statewide Health and Development (OSHPD). Notes: Price is derived from 1995 data that is adjusted from age, severity of illness, race, DRG, type of admission and number of other diagnosis. Bootstrapped standard errors using 1000 replications are reported in parenthesis.
Table 7: Stanford and UCSF in 1996

<table>
<thead>
<tr>
<th>Hospital</th>
<th>City</th>
<th>Premerger Price</th>
<th>Postmerger Price</th>
<th>Price Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mount Zion Med Center</td>
<td>San Francisco</td>
<td>$2,642</td>
<td>$2,670</td>
<td>1.06%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.31)</td>
</tr>
<tr>
<td>Univ. of Cal Med Center</td>
<td>San Francisco</td>
<td>$4,813</td>
<td>$4,841</td>
<td>0.59%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.18)</td>
</tr>
<tr>
<td>Stanford Health Services</td>
<td>Stanford</td>
<td>$4,253</td>
<td>$4,286</td>
<td>0.77%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.23)</td>
</tr>
</tbody>
</table>

Notes: OSHPD data. Bootstrapped standard errors of percent change in price using 1000 replications are reported in parenthesis.
<table>
<thead>
<tr>
<th>Hospital</th>
<th>City</th>
<th>Premerger Price</th>
<th>Postmerger Price</th>
<th>Percent Change in Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alta Bates Medical Center</td>
<td>Berkeley</td>
<td>$5,238</td>
<td>$5,646</td>
<td>7.79%</td>
</tr>
<tr>
<td>Summit Medical Center</td>
<td>Oakland</td>
<td>$3,893</td>
<td>$5,099</td>
<td>30.97%</td>
</tr>
<tr>
<td>Eden Medical Center</td>
<td>Castro Valley</td>
<td>$3,540</td>
<td>$3,703</td>
<td>4.61%</td>
</tr>
<tr>
<td>Sutter Amador Hospital</td>
<td>Jackson</td>
<td>$4,847</td>
<td>$4,848</td>
<td>0.01%</td>
</tr>
<tr>
<td>Sutter Delta Medical Center</td>
<td>Antioch</td>
<td>$5,542</td>
<td>$5,556</td>
<td>0.26%</td>
</tr>
<tr>
<td>Sutter Coast Hospital</td>
<td>Crescent City</td>
<td>$4,743</td>
<td>$4,743</td>
<td>0.01%</td>
</tr>
<tr>
<td>Sutter Lakeside Hospital</td>
<td>Lakeport</td>
<td>$4,905</td>
<td>$4,906</td>
<td>0.00%</td>
</tr>
<tr>
<td>Marin General Hospital</td>
<td>Greenbrae</td>
<td>$5,293</td>
<td>$5,317</td>
<td>0.45%</td>
</tr>
<tr>
<td>Novato Community Hospital</td>
<td>Novato</td>
<td>$4,769</td>
<td>$4,787</td>
<td>0.37%</td>
</tr>
<tr>
<td>Los Banos Community Hospital</td>
<td>Los Banos</td>
<td>$4,101</td>
<td>$4,101</td>
<td>0.01%</td>
</tr>
<tr>
<td>Sutter Merced Medical Center</td>
<td>Merced</td>
<td>$2,628</td>
<td>$2,628</td>
<td>0.01%</td>
</tr>
<tr>
<td>Sutter Auburn Faith Hospital</td>
<td>Auburn</td>
<td>$5,229</td>
<td>$5,229</td>
<td>0.01%</td>
</tr>
<tr>
<td>Sutter Roseville Medical Center</td>
<td>Roseville</td>
<td>$1,068</td>
<td>$1,069</td>
<td>0.14%</td>
</tr>
<tr>
<td>Sutter General Hospital</td>
<td>Sacramento</td>
<td>$3,510</td>
<td>$3,510</td>
<td>0.02%</td>
</tr>
<tr>
<td>Sutter Memorial Hospital</td>
<td>Sacramento</td>
<td>$3,546</td>
<td>$3,547</td>
<td>0.01%</td>
</tr>
<tr>
<td>California Pacific Medical Center</td>
<td>San Francisco</td>
<td>$4,466</td>
<td>$4,506</td>
<td>0.92%</td>
</tr>
<tr>
<td>Sutter Tracy Community Hospital</td>
<td>Tracy</td>
<td>$4,333</td>
<td>$4,342</td>
<td>0.21%</td>
</tr>
<tr>
<td>Mills-Peninsula Health Services</td>
<td>Burlingame</td>
<td>$4,339</td>
<td>$4,347</td>
<td>0.18%</td>
</tr>
<tr>
<td>Sutter Sonoma Medical Center</td>
<td>Santa Rosa</td>
<td>$4,408</td>
<td>$4,411</td>
<td>0.08%</td>
</tr>
<tr>
<td>Memorial Medical Center</td>
<td>Modesto</td>
<td>$3,422</td>
<td>$3,424</td>
<td>0.05%</td>
</tr>
<tr>
<td>Sutter Davis Hospital</td>
<td>Davis</td>
<td>$4,518</td>
<td>$4,519</td>
<td>0.03%</td>
</tr>
</tbody>
</table>

Notes: OSHPD data. Bootstrapped standard errors of percent change in price using 1000 replications are reported in parenthesis.
8 Appendix

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:

\[
\Theta^{\text{pre}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \rightarrow \Theta^{\text{post}} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}
\]

The pre-merger prices for the 3 firms are:

\[
p^{\text{pre}}_1 = MC_1 - D_1 \frac{\partial D_1}{\partial p_1}
\]
\[
p^{\text{pre}}_2 = MC_2 - D_2 \frac{\partial D_2}{\partial p_2}
\]
\[
p^{\text{pre}}_3 = MC_3 - D_3 \frac{\partial D_3}{\partial p_3}
\]

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

\[
p^{\text{post}}_1 = MC_1 - D_1 \frac{\partial D_1}{\partial p_1} + \left( p^{\text{post}}_2 - MC_2 \right) \frac{\partial D_2}{\partial p_1} \frac{\partial D_2}{\partial p_2} \frac{\partial D_2}{\partial p_1} 
\]
\[
p^{\text{post}}_2 = MC_2 - D_2 \frac{\partial D_2}{\partial p_2} + \left( p^{\text{post}}_1 - MC_1 \right) \frac{\partial D_1}{\partial p_2} \frac{\partial D_2}{\partial p_2} 
\]

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.\(^{18}\)

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

\[
p_j - MC_j = - D_j \frac{\partial D_j}{\partial p_j}
\]

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

\[
p^{\text{post}}_1 \approx MC_1 - D_1 \frac{\partial D_1}{\partial p_1} - \left[ \frac{D_2}{\partial D_2/\partial p_2} \right] \frac{\partial D_2}{\partial D_1/\partial p_1}
\]

\(^{18}\)The approximation we use can be the first iteration solving for the true equilibrium. Thus this is a “first-order” method of approximation.
The expression for firm 2 is symmetric. We can thus calculate the approximate merger price effect as:

$$p_{1}^{\text{post}} - p_{1}^{\text{pre}} \approx \left[ \frac{D_2}{\partial D_2/\partial p_2} \right] \frac{\partial D_2}{\partial D_1/\partial p_1}$$

(17)

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

$$p_{1}^{\text{post}} - p_{1}^{\text{pre}} \approx \frac{1}{\alpha} \frac{1}{\Lambda_2} \frac{1}{\alpha} \sum N_t Pr(t\rightarrow 2) Pr(t\rightarrow 1)$$

(18)

This simplifies to the final form:

$$p_{1}^{\text{post}} - p_{1}^{\text{pre}} \approx \frac{1}{\alpha} \frac{1}{\Lambda_2} \sum N_t Pr(t\rightarrow 2) Pr(t\rightarrow 1)$$

(19)

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 (19). 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:

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

(20)

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:

$$p_{1}^{\text{post}} - p_{1}^{\text{pre}} \approx \frac{1}{\alpha} \frac{\Lambda_{12}}{\Lambda_2}$$

(21)

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

$$\frac{p_{1}^{\text{post}} - p_{1}^{\text{pre}}}{p_{1}^{\text{pre}} - MC_1} \approx \left[ \frac{1}{\alpha} \frac{\Lambda_{12}}{\Lambda_2} \right] \frac{\Lambda_{12}}{\Lambda_1}$$

(22)

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.
Table A.1: Regression Results, LOCI (1995)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model (1)</th>
<th>Model (2)</th>
<th>Model (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wage Index</td>
<td>2227.12***</td>
<td>2456.82***</td>
<td>2387.19***</td>
</tr>
<tr>
<td></td>
<td>(632.35)</td>
<td>(638.15)</td>
<td>(632.89)</td>
</tr>
<tr>
<td>Teaching Status</td>
<td>766.83***</td>
<td>923.62***</td>
<td>876.10***</td>
</tr>
<tr>
<td></td>
<td>(262.88)</td>
<td>(275.88)</td>
<td>(280.87)</td>
</tr>
<tr>
<td>Technology Index</td>
<td>-5.46</td>
<td>-2.42</td>
<td>-3.34</td>
</tr>
<tr>
<td></td>
<td>(16.56)</td>
<td>(17.15)</td>
<td>(16.91)</td>
</tr>
<tr>
<td>Nonprofit</td>
<td>-378.51*</td>
<td>-362.97</td>
<td>-367.68</td>
</tr>
<tr>
<td></td>
<td>(229.02)</td>
<td>(234.27)</td>
<td>(232.55)</td>
</tr>
<tr>
<td>For-Profit</td>
<td>284.61</td>
<td>541.50*</td>
<td>463.63</td>
</tr>
<tr>
<td></td>
<td>(270.72)</td>
<td>(313.30)</td>
<td>(315.56)</td>
</tr>
<tr>
<td>inverse LOCI</td>
<td>446.59***</td>
<td>885.05***</td>
<td>752.15***</td>
</tr>
<tr>
<td></td>
<td>(114.95)</td>
<td>(233.10)</td>
<td>(243.72)</td>
</tr>
<tr>
<td>Intercept</td>
<td>1884.55***</td>
<td>809.69</td>
<td>1135.50</td>
</tr>
<tr>
<td></td>
<td>(690.48)</td>
<td>(858.10)</td>
<td>(856.93)</td>
</tr>
</tbody>
</table>

*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: Data is same as in Gaynor and Vogt (2003). Standard errors are reported in parentheses. Significance levels *: 10%, **: 5%, ***: 1%