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Abstract

The hospital competition literature demonstrates that estimates of the effect of local market structure on competition are sensitive to geographic market definition. Our spatial lag approach effects smoothing of the explanatory variables across the discrete market boundaries. This approach results in robust estimates of the impact of market structure on hospital pricing, which can be used to estimate the full effect of changes in prices inclusive of spillovers that cascade through the neighboring hospital markets. In markets where concentration is relatively high before a proposed merger, we demonstrate that OLS estimates can lead to the wrong antitrust policy conclusion while the more conservative lag estimates do not.

I. Introduction

Hospital competition is a function of market extent—the geographic space in which all relevant competitors reside—and that space is, in the long run, endogenous. Hospitals choose location and product dimensions, and contractual arrangements with payers and other hospitals that directly impact the competition they face and extent of the relevant market. The elasticity of demand facing a hospital is a function of their product mix as well as their constituents' willingness to travel to hospital. Because distance to hospital is such a strong determinant of demand, and because consumers are geographically dispersed, two or more hospitals may compete for constituents who live in particular markets. This market contestability over geographic space has been called the 'relational aspect' of hospital markets, which makes them difficult to define with discrete market boundaries (Dranove and Shanley, 1989).

It is well known that drawing market boundaries that do not perfectly contain all relevant competitors can impart bias on the estimated effects of structural competition measures (i.e. number of firms, concentration of firms market shares) on market outcomes (Scherer and Ross, 1990, pp 422-424; Pindyck and Rubinfeld, 1998). Economists have spent a great deal of time considering better ways to measure market extent for antitrust purposes (Elzinga and Hogarty, 1974; Dranove, Shanley, and Simon, 1992; Frech, Langenfeld, and McCluer, 2004). Recent efforts have focused on using demand substitution parameters defined from hospital choice models (Kessler and McClellan, 2000; Gaynor and Vogt, 2000; Capps, Dranove, Greenstein, and Satterthwaite, 2001).

Capps et al make explicit the impact of travel elasticity of demand on overall demand elasticity of substitution, which is a key parameter in the dynamics of hospital competition. Capps et al (2001) posit that price elasticity of demand (η_j^d)is directly proportional to the elasticity of time (η_j^t) spent by patients traveling to hospital:

$$\eta_j^d = K_j \, \eta_j^t \text{, where } K_j > 0. \qquad (1)$$

A decrease in either elasticity is associated with higher market power, thus if a merger between two hospital succeeds in reducing the time elasticity of demand, it will increase market power for the merged hospitals. Reducing the time elasticity would mean making consumers less sensitive to distance. This might happen if the merged facilities segmented the market, specializing in particular high-tech services, and reduced the cost/improved the quality of these services. Market power against payers would increase because of specialization – hospitals would become more heterogeneous, and the quality of care would increase making consumer demand less elastic (more loyal).

Our focus here is not on defining the relevant hospital market. We are concerned with obtaining a consistent estimate of the impact from hospital market structure (concentration) on hospital pricing. We use a Nash model of hospital rivalry to motivate the use of a spatial interaction model in estimating the effect of market structure on hospital pricing. We estimate a spatial lag model to attempt a separate identification of the effect of structural characteristics at the local level and spatial interaction among competing hospitals. Because the spatial market unit is smaller than the actual range of spatial interaction, spatial autocorrelation is present in the data, which complicates the separate identification of true spatial interaction from spatial mismatch effects. However, by incorporating the spatial lag in the model, the effect of the local market characteristics on equilibrium prices is estimated consistently. We contrast this specification with ordinary least squares (OLS), where the effect of spatial interaction is ignored and the estimated effects of local characteristics are biased, with misleading standard errors. Our spatial econometric methods also help to avoid problems associated with using fixed market boundaries, but contrasts with recent approaches in the literature that do not consider spatial autocorrelation.

The rest of this paper is organized as follows. Following Mobley (2003) we briefly describe the Nash bargaining theory of hospital pricing and associated price reaction functions with slopes that reflect degree of hospital interaction. We then show how competing hospital characteristics - reflecting the degree of specialization or substitutability - can impact the slope of price reaction functions, making explicit the role of time-travel elasticity of demand. Mobley (2003) did not consider the time-travel elasticity as a dimension reflecting the competitive environment facing hospitals. We then develop an empirical model that incorporates hospital interaction and estimate it using spatial regression methods. We then interpret the findings in the context of analysis of competition in hospital markets. We conclude with some limitations and directions for future research.

II. The Theoretical Model

The theoretical model was fully developed by Mobley (2003) so only an abbreviated version is given here. The theoretical model of hospital interaction is a Nash bargaining model that derives from standard oligopoly theory of price reactions among rivals. Oligopoly is the correct industry construct for this study, because (with the exception of large teaching hospitals and specialty hospitals) California hospital markets are quite local (Mobley and Frech, 2000). Thus we define the most relevant competitors for each short-term general, acute-care hospital in our sample as those hospitals in closest geographic proximity.

The oligopoly model employs price-reaction functions, showing each firm's price response to what they anticipate their rivals will do (Krouse, 1990). When all firms in a market simultaneously optimize profits, their price reaction functions characterize the equilibrium that obtains. We assume that firms choose price structures to maximize profits, and the first-order condition at the profit maximum is used to derive the price-reaction function. The price-reaction function depends upon industry conditions (cost C, demand P) and conjectures held by firms regarding what they expect their rivals will do (Φ). The stationarity condition at the profit maximum is solved to find each firm j's price-reaction function, P_j*, in response to prices set by other firms (k):

$$P_j* = r_j (P_k; \Phi_{kj}; C_j) \tag{2}$$

The intersection of the firms' reaction functions is a feasible price pair characterizing the equilibrium. Implicit differentiation of the stationarity condition can be used to derive the slope of the reaction function, which is positive when products are substitutes and demand is linear or not too convex (Krouse, 1990). The more specialized a hospital is relative to its competitors, the less substitutable are their services, and its reaction function has a flatter slope. For perfect substitutes, the slope is unity, and the reaction functions coincide with an equilibrium price at the most competitive level (Carlton and Perloff, 1994, p. 247). If time-travel elasticity is proportional to product demand elasticity (Capps, Dranove, Greenstein, and Satterthwaite, 2001), then a decrease in the willingness to travel would decrease the elasticity of substitution, flattening the reaction functions and making hospitals poorer substitutes as they become more distant from one another.

Figure 1 demonstrates that the flattening slopes result in higher equilibrium prices, as competition is reduced by the spatial differentiation. With perfect collusion, the reaction curves cross at the highest possible price set that could be sustained by the market (Figure 2). Thus our estimate of the slope of the price reaction function reflects the elasticity of substitution among hospitals, which is sensitive to the time travel elasticity of consumers. The slope of the reaction function is a direct measure of the degree of competition among hospitals in the market.

III. Background and Data

This study uses financial data from California hospitals, which are known to face strong price competition from rivals and are important from a market or antitrust perspective because of their considerable merger activity in the past decade (Jones 1999; Mobley, 2003; 1997; 1995). Recent hospital antitrust decisions reflect the opinion that mergers are viable strategies for reducing competition (Simon, 2005), and California hospital markets are very competitive (Frech and Mobley; 2000; Mobley, 2003; 1998; 1995).

Most California hospital markets are very urban, and land use patterns are dense, with small distances between competing hospitals. The vast majority of hospital inpatients traveled less than 20 miles to hospital (Mobley and Frech, 2000). Managed care plans solicit competitive price bids from competing hospitals, who offer volume discounts to get all of the business from the managed care plans. As Medicare fee-for-service payment rates have become less profitable, and Medicare has promoted use of 'Medicare' managed care plans (offered by private insurers), private insurance plans have become important players with considerable market power. Thus price competition is an important aspect of the market environment in California.

To study interaction among hospitals in their pricing decisions, we obtained data from several sources: hospital financial and discharge data are from California's Office of Statewide Health Planning and Development (OSHPD); information about multi-hospital chain ownership is from the AHA *Guide* and *Hospital Statistics*; and for codes describing the integration between hospital and physicians are from the AHA *Annual Survey of Hospitals*. The urban-continuum codes used for defining highly urbanized versus other places are from the February 1998 ARF (*Area Resource File)*. The outcomes-based quality variable we use is based on the study of acute myocardial infarction (AMI) by OSHPD (OSHPD, 1997).

We use hospital financial and discharge data from the year 1998 for 336 short-term general hospitals. Actual contract prices are not available, so we use for our dependent variable net (of contractual discounts with payers) inpatient revenue received from private payers per private inpatient day, adjusted to reflect outpatient care. This price variable reflects the average negotiated prices for privately insured hospital patients, and is a good proxy for prices in this selective contracting environment, reflecting income actually received by hospitals for the broad range of services provided to privately insured patients.

The variables central to this study reflect competitive market conditions that affect the balance of power in the hospital's market. These variables are thought to shift the reaction functions rather than impact their slopes directly, affecting equilibrium prices (Mobley 2003). Competitive market conditions include hospital organizational structure (whether they are affiliated with a multihospital chain, their ownership type), hospital market concentration (the concentration of hospital business into a few versus many firms, a measure of competition), the extent of vertical integration between hospitals and physicians (which could impact market power in bargaining with insurers), and managed care penetration in the local hospital market. Higher managed care penetration in the market indicates that a greater proportion of business is contractually negotiated, thus price competition is greater in these highly-penetrated markets. For defining the market-level factors, we employ a very local measure of market extent, the Health Facilities Planning Area (HFPA). The HFPA areal unit was defined by the state of California to reflect self-contained hospital markets based on flows of resources and commerce. The HFPAs are smaller and more numerous than counties.

We define a Herfindahl index of market-level concentration (and a measure of managed care penetration) using the traditional fixed-boundary approach. That is, we measure market concentration using the Herfindahl index (HHI), defined over market shares in net patient revenue at the hospital's HFPA level. In constructing the index, hospitals in an HFPA affiliated with the same multihospital chain are treated as a single unit in measuring market share, so chain penetration affects our Herfindahl statistic. We also include in our regression a centered measure of market share (CENTSHARE) following Keeler, Melnick, and Zwanziger (1999, p. 76). The coefficient of

CENTSHARE captures the impact of size relative to the average size in the hospital's HFPA, while the coefficient of HHI shows the effect of competition independent of the hospital's size. Managed care penetration is measured at the HFPA level using two variables derived from patient discharge data: the proportion of patient discharges in managed care plans exclusive of the Kaiser plans (MANGCARE), and the Kaiser plans' market share (KAISER SHARE).

For the organizational structure measures, we distinguish secular from non-secular chains by defining multihospital chain ownership in three categories: for profit, non-profit secular, and non-profit religious (FPCHAIN, NPCHAIN, RCHAIN). We define hospitals' vertical integration with physician groups (LOOSE, TIGHT) following Burns, Bazzoli, Dynan and Wholey (1998). Burns et al. define "tight" versus "loose" integration arrangements between hospitals and physicians, using the AHA physician integration codes. "Tight" integration includes management service organization, foundation, group practice without walls, equity model, and integrated salary model forms of integration. "Loose" integration includes independent practice associations (IPAs) and physician hospital organizations (PHOs). These two groupings are defended in related empirical research which documents the existence of distinct groupings based on the intensity of process-level interactions among hospitals and physicians (Dynan, Bazzoli, and Burns, 1998).

To isolate the main competitive effects, we also control for several factors that do not affect the balance of power *per se* but might impact the hospital's offered price, such as indigent care burden (LOSSES/EXPEND), casemix complexity (CASEMIX), Medicare prospective payments system (PPS) pressure in the hospital (PPS PRESSURE), and hospital size/the number of available beds in the hospital (BEDS), and measures of urban intensity (POPDEN, URBAN). In order to hold constant variation in price due to demand for process quality and complexity of care, we include payroll expenses per adjusted inpatient day (DLEVEL) and an index of the breadth of services offered (SCOPE) as additional control variables. Our outcomes-based quality measure, (WORSE) indicates hospitals that performed significantly worse than expected in acute myocardial infarction care, based on a careful quality study with findings announced to the public in 1993 (OSHPD, 1997). Because some of these hospital-specific explanatory variables may themselves be affected by hospital prices, thus raising concerns about endogeneity, these are lagged two years.

IV. The Econometric Spatial Lag Model of Hospital Pricing Interdependence

The econometric model recognizes the interdependence of hospitals' pricing decisions in an equilibrium context. When we define a spatial lag process to characterize the degree of product substitution (competition) in the market, we assume that hospitals in closer proximity are closer substitutes than those more distant. The closest neighbors are defined using a spatial weights matrix (W). These neighbors' pricing decisions directly impact a hospital's pricing decision. But because space is multidirectional (not linear), hospitals share neighbors with other hospitals, and the pricing spillovers are a simultaneous, non-linear phenomenon. Ultimately, each hospital is impacted by many others in the system, with influence diminishing with distance. The simultaneity and non-linearity of these spillovers is captured in the spatial lag model specification and estimation.

The price reaction function specified above by our Nash bargaining model (equation 2) depends upon behavior (Φ) and on demand and cost conditions (P,C). This strategic-interaction model of hospital behavior is appropriate whenever hospitals in close proximity make interdependent choices. Interdependence means that one hospital's choice directly impacts the choices made by neighbors (as distinct from situations wherein apparently similar behaviors arise from concerted response to some common neighborhood effect). Empirical support for the theory of pricing interaction can be provided from specification tests, which we discuss below Table 4. Mapping equation 2 into a linear estimable form, the spatial lag model can be written:

$$P^* = \rho WP + X\beta + u \qquad (3)$$

The vector P is hospital price and the ρWP term on the right side of the equation is the spatial lag term. The model specification reflects spatial spillovers in pricing: each hospital's price P is in part determined by average prices among the neighboring hospitals (ρWP), and (with influence declining with distance) all other hospitals in the system. The estimate of the spatial lag parameter (ρ) reflects the slope of the reaction function, which parameterizes the degree of interdependence in pricing, i.e. how much hospital i's price is influenced by the average prices of immediate (and more distant) neighbors. Examples from the literature of positing the lag parameter as the slope of the reaction function include models of adoption of innovation among farmers (Case, 1992), expenditures by states on public goods (Case, Rosen, and Hines, 1993), models of tax competition and welfare competition among local governments (Brueckner and Saavedra, 2001; Saavedra, 2000), strategic interaction among cities (Brueckner, 1998; 2003), and the endogeneity of land use patterns (Irwin and Bockstael, 2002; 2004).

In equation 3, the behavior, demand, and cost conditions are subsumed in the vector X, which includes contextual factors that can shift the reaction functions. These contextual factors include structural measures characterizing the insurance, hospital, and physician markets. These groups provide the market climate for the rivalry that ultimately determines the equilibrium negotiated prices between private payers and hospitals. Mobley (1995) showed that the behavioral parameter (Φ) may be impacted by multihospital chains, which provides a profit-maximizing rationale for merger or acquisition under multihospital ownership. Multihospital chain ownership, insurance market structure, and vertical integration of physician groups within hospitals are factors included in the model to reflect these contextual factors. Table 1 describes the variables included in the empirical estimation with a brief rationale for inclusion for each.

Simultaneous System and Spatial Smoothing of Explanatory Variables

Because all hospitals' prices are determined simultaneously in equilibrium, the term WP on the right-hand side of (3) will be correlated with the error term. In estimating equation 3, the simultaneity embedded in the WP term must be explicitly accounted for, either in a maximum likelihood framework, or by using a proper set of instrumental variables. To demonstrate this simultaneity, we solve (3) for the equilibrium price vector P*, given by the reduced form:

$$P^* = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} u \qquad (4)$$

The matrix inverse $(I - \rho W)^{-1}$ is a full inverse, which yields an infinite series that involves error terms at all locations: $(I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \ldots)u$. Each location is correlated with every other location, but this decays with the order of contiguity (the powers of W in the series expansion). Powers to the weights matrix (W^2, W^3, etc.) reflect neighbor sets in more and more remote contiguity (i.e., second order contiguity is one's neighbors' neighbors, and third order is one's neighbor's neighbor's neighbors, and so forth). The spatial lag term ρW for observation j is correlated with its own error u_j, and with all other errors in the system.

Equation 4 shows that the spatial lag model allows global spatial autocorrelation in both the explanatory variables and the error term. This means that the dependent variable is explained by local variables (in the hospital's own market, the HFPA) as well as all others in the system, following a general distance decay pattern, as expanded in equation 5:

$$E\,[P \mid X] = X\beta + \rho WX\beta + \rho^2 W^2 X\beta + \ldots u \qquad (5)$$

In equation 5, Because $|\rho|<1$, each successive term in the expansion has smaller and smaller impact, characterizing less and less influence from observations more and more distant. This expression is useful because it shows that explanatory factors defined at the discrete HFPA market level (i.e., managed care penetration or hospital concentration) are spatially smoothed across local markets. Thus the expected equilibrium price is determined by each hospitals' own market factors as well as those of immediate neighbors (ρWX) and second order neighbors ($\rho^2 W^2 X$) and so forth.

To see how constructing the spatial lag of the Herfindahl index (HERF97) smoothes it, relative to the raw index, we use a Moran's I plot in Figure 3. A Moran's I scatter plot is a plot with the variable of interest (HERF97) on the x-axis and the spatial lag (W_HERF97) on the y-axis. Anselin (1996) describes the use of this type of plot to assess local instability in spatial association. In our data, each hospital in the sample is represented by a point, with the Herfindahl index for its HFPA plotted against its spatially lagged value, which is an average of neighboring hospitals' Herfindahl values. In Figure 3, the slope of the regression line (0.389, top panel) is the Moran's I statistic for HERF97, using a six-closest neighbors weights definition. If the hospital's HERF97 were identical to its neighboring hospitals' HERF97 values, then the Moran's I statistic would be near 1. When neighbors have greater dissimilarity in the HERF97 values, the value of Moran's I is lower, and conversely. In Figure 3, we plot the relationships between hospitals' HERF97 values and the average HERF97 value for their spatial neighbors, using the seven closest neighbors to form the spatial lag. Figure 3 shows that the Moran's I value is close to 0.40, which indicates considerable similarity with neighbors but not perfect agreement. Thus having the closest-neighbors HERF97 (lagged HERF97) in the econometric system adds information which effectively smoothes over the discrete market boundaries imposed by the HFPAs.

The spatial lag Herfindahl index is weighted by the spatial lag parameter, which cannot exceed unity. For neighbors of neighbors, a second-order spatial lag is calculated from the Herfindahl indices of neighbors' neighbors, which is given less weight (the squared spatial lag parameter). For neighbors' neighbors' neighbors, a third-order effect is calculated, and so forth. Thus the spatial lag model effects smoothing of contextual factors over discrete market boundaries, using information from the hospital's HFPA, augmented by information about neighboring hospitals' HFPAs, with greater weight given to closer neighbors.

Empirical Results: Marginal versus Full Effects

The spatial lag econometric model is appropriate when there is a theoretical model of the structural interaction among hospitals determining equilibrium prices, and one is interested in measuring the strength of that interactive relationship. The spatial lag econometric model is equally relevant when one is interested in obtaining consistent estimates of the marginal impacts of explanatory variables on equilibrium price, in the presence of spatial spillovers in pricing (Kim, Phipps, and Anselin, 2006). In the equilibrium framework, the marginal impact is the partial derivative, or change in own price holding all others' prices constant. The total derivative would be the combined effect of all hospital price changes in the simultaneous equilibrium.

From the reduced form (equation 4), we see that the marginal impact of a unit change in X on P is not simply β, as it would be in the OLS model. The spatial lag model specification modifies the impact of X on P through the matrix inverse term $(1-\rho W)^{-1}$. This modification accounts for spatial correlation among the Xs and spillover effects ρ (the fact that every hospital's response to a shock is recognized and anticipated by neighbors, who then respond in turn). Thus, the spatial lag model estimate of β obtained after spatially filtering the dependent variable is a consistent estimate of the direct, or marginal, impact of X on P in the equilibrium for the system.

If there is spatial autocorrelation in the data, estimation of equation 3 by OLS (thus excluding the endogenous WP term) would fail to separate the marginal effects of the variables X on price. In that case, and when ρ is positive:

$$E[P \mid X] = X\beta_{ols}, \text{ and } \quad |\beta_{ols}| > |\beta| \qquad (6)$$

β_{ols} will be biased upwards in magnitude whenever the variable X for hospital i is spatially correlated with the X variables for their neighboring hospitals (Anselin, 2003). In the empirical results given in Table 2, the magnitude of this bias (on average, $1/(1-\rho)$) is illustrated by comparing the OLS and spatial lag models' estimates.

V. Discussion: Application of the Spatial Lag Model to Hospital Pricing

In the empirical modeling, we characterize contextual market conditions with market-specific variables, defined over circumscribed HFPA regions, while true "competition" (spatial interaction) is captured with the spatial lag econometric specification. Thus we assume explicitly by our modeling strategy that competition is something simultaneous that occurs among hospitals, and that these other measures are more indicative of factors that can tilt the balance of power in favor of either suppliers (physicians) or payers (insurers). We use very local market (HFPA) measures of these conditioning factors, recognizing that when the fixed market definition under-bounds the true range of spatial interaction, the market variables will be spatially correlated. However, the spatial correlation of market conditioning variables is accounted for explicitly in our estimation. It is worth noting that the opposite case—over-bounding the market—can hide valuable information through aggregation. Because of this, we see the strategy of very local market definition coupled with spatial econometric modeling as an ideal partnership in preserving and using information in the data.

Table 2 contains results from estimation of three different specifications of the hospital pricing model: an ordinary least squares regression model with no accounting for spatial spillovers, a spatial lag model using the seven-closest neighbor specification of spatial weights, and a spatial lag model using an inverse distance function to specify the spatial weights. Table 3 contains sample statistics, and Table 4 provides diagnostic tests demonstrating the validity of the lag model under different specifications of neighbor sets. Table 2 shows that there is statistically significant evidence of a spatial lag process in prices (p-val 0.006), and the estimate of the spatial lag parameter (ρ) is 0.231 for the seven-closest neighbor model. For the inverse-distance model, the spatial lag estimate is 0.278 with a p-value of 0.046.

The Spatial Multiplier Effect in Hospital Pricing

In the context of our work, the spatial lag model captures through the spatial multiplier process both the direct (marginal) and indirect (spillover) effects of a neighborhood's hospital characteristics, including market conditions, on equilibrium prices. A shock in the contextual variable X is felt simultaneously by all hospitals in the neighborhood, rather than being felt primarily by a single hospital with a ripple effect through the neighborhood. The ripple effect is due to model structure (lag), the specification of the neighbor weights (how many neighbors) and the magnitude of the spatial autoregressive coefficient. Anselin (2003) describes the global spatial multiplier, ($1/1-\rho$), as the average extent to which the direct effect of a factor on the dependent variable is magnified by the spillovers in the system. The parameter which defines the magnitude of the ripple effect is the spatial lag, which compounds spillovers through the spatial multiplier. Thus the estimated coefficients in the spatial lag model are consistent estimates of the marginal effect of a change in X on equilibrium prices, while the full effect is a multiple of the marginal effect.

For example, in hospital pricing (Table 2), the global spatial multiplier is 1.30 for the seven-closest neighbor model. Thus almost 1/3 of the impact of competition on prices is already reflected in neighborhood prices, through indirect reaction effects from neighbors. In other words, every dollar impact of an X variable on equilibrium price derives about a third of its effect from interaction among hospitals within the system. Failure to account for the redundancy or commonality in shocks through muting the indirect effects (OLS model) would lead to inflation of about 18% in the estimated marginal impact of concentration on equilibrium prices. Thus the OLS estimates of the direct (marginal) impacts of competition variables are biased upwards in magnitude, because the model is misspecified by omission of spatial spillover effects. In sum, the spatial lag model accounts for the redundancy induced by spatial autocorrelation in explanatory variables as well as spillover effects (interactions) among hospitals that lead to interdependence in hospital pricing behavior. OLS estimation ignores these things, and can produce biased estimates of the marginal, or direct, effects of market competition variables on equilibrium prices, and produces misleading standard errors.

The theory of spatial spillovers can be supported by empirical tests that distinguish between a spatial lag and a spatial error process (Anselin and Bera, 1998, p. 279). The test results in Table 4 support the theory of spatial spillovers in pricing, as the spatial lag model is a better fit to the data than the alternative (a spatial error model). Further, we believe this finding is robust, because the spatial lag process is consistently more significant than the spatial error process for several different sets of spatial weights (i.e., k=5, k=6, k=7, and k=8 closest neighbors, inverse distance, and binary distance weights).

VI. Implications of Findings for Hospital Competition and Market Definition

For hospital competition analysis, *market concentration* is a key construct. This construct reflects the dispersion of market share among one, few, or many firms, and is a larger number when the shares are distributed into fewer firms. Greater concentration is associated with greater power of firms to influence market prices. The most widely used measure is the Herfindahl Index (HHI), which is actually the sum of squared market shares (giving greater weight to larger firms). In our analysis, the local market is the HFPA, so the HHI is the sum of squared market shares for all hospitals inside each HFPA, resulting in a single measure of concentration for each HFPA.

For competition analysis, the full effect of market concentration (HHI) on price is the appropriate estimate. The full effect includes both the direct, first-round impact as well as additional feedback from changing prices in neighboring markets (spillovers). To calculate this full effect, we multiply the spatial lag estimate of the marginal impact from concentration on price (the beta coefficient) by the spatial multiplier ($1/1-\rho$). For the seven-nearest neighbor model, the full effect estimate is 369.47; for the inverse distance model, it is 391.26. These empirical results have strong implications for the definition of hospital markets for antitrust purposes.

In recent years, antitrust market definition in the United States has been influenced by the Guidelines issued by the U.S. Department of Justice and the Federal Trade Commission, who have jointly issued merger guidelines, revised several times over the years (Langenfeld, 1996; Werden, 2003). The Guidelines view geographic markets from the perspective of a hypothetical monopolist, calling for a 'thought experiment' where all of the producers of a given product within a geographic area collude on price and become, hypothetically, a local monopolist. Then, the relevant geographic market for antitrust purposes is defined to be the smallest geographic area such that this hypothetical monopolist would be able to implement about a 5 percent price increase.

The ultimate policy goal is to prevent mergers from increasing market power. From this viewpoint, the harm of market power is an increase in price, regardless of whether it comes from spatial interactions extending beyond the putative market. Indeed, the competitive harm is greater if the ultimate increase in price above the competitive level extends outside of the geographic market. This analysis implies that the correct model for this purpose must capture the full feedback from other areas.

Our results can be easily interpreted in terms of the hypothetical-monopolist thought experiment. Suppose we consider a market with a Herfindahl index (HHI) measure of 0.468, which is the mean for our sample (Table 3). The hypothetical monopolist would be perfect collusion of all firms in the local market, acting as a single monopolist, leading to an HHI measure of 1.0. Therefore, the predicted price increase caused by raising the HHI from 0.468 to 1.0 is a direct empirical estimate of the price increase resulting from the hypothetical monopolist thought experiment. If this predicted price increase exceeds the 5 percent of the Guidelines, then the area (HFPA) over which we defined the Herfindahl index is larger than the appropriate *antitrust* market.

The coefficient on concentration in the seven-nearest neighbors spatial lag equation is 284.21. This is the partial effect. To find the estimate of the full effect, one must multiply by the global multiplier, 1.30, giving 369.47. If the hypothetical monopolist organized all the hospitals in this typical market into a monopoly the predicted price increase from the hypothetical monopolist example is:

$$\Delta Price = \Delta HHI * \beta_{HHI} = (1.0-0.468) * 369.47 = \$196.56. \qquad (7)$$

Since the mean price is $1543.94, the percentage price increase would be about 13 percent, which still vastly exceeds the 5 percent of the Guidelines, indicating that HFPAs are larger (on average) than actual *antitrust* markets. Using the lower OLS coefficient estimate ($335.116), the estimated impact on price would be about 11.5 percent, yielding the correct conclusion *in this case.* However, in a less competitive market at the onset, i.e. moving from a HHI of 0.75 to 1.0, the OLS estimate is 5% while the lag estimate is 6%, thus the OLS analysis would conclude 'no harm' when in fact the guidelines had not been met. Thus in market situations where competition is lower to start with, the bias in the OLS estimates can yield wrong decisions. These are the situations that usually wind up in antitrust court, so the importance of these findings should not be ignored.

VII. Conclusion

There has been continued interest in the health economics literature in modeling hospital market competition and in understanding and explaining competitive effects. The model of spatial interaction presented in this paper is concerned with characterizing the essence of competition itself. With our direct modeling of the range of competitive interaction, we then obtain consistent estimates of the impact of local market structural characteristics on the equilibrium prices that arise from the competitive interaction among hospitals. Using this, we demonstrate the potential problems that might arise when using OLS estimates instead of more robust lag estimates in the assessment of potential harms from merger. In cases where the market if highly concentrated before merger, we show that OLS estimates can lead to the wrong policy conclusions.

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Table 1: Variable Definitions

Variable	Description	Rationale for Inclusion
PPS PRESSURE	Proportion of net patient revenue from Medicare (a proxy for Prospective Payments System pressure)	Reduces a hospital's ability to price competitively in the private market
LOSSES/EXPEND	Bad debt and charitable services (net of gifts) as a share of total operating expense	Reduces a hospital's ability to price competitively in the private market
SCOPE	Index of the breadth of hospital services offered	Increases a hospital's ability to attract demand in the private market
CASEMIX	index of disease complexity in the inpatient population	Increases hospital costs
DLEVEL	Proxy for demand intensity: total payroll per inpatient day, lagged two years	Increases a hospital's ability to attract demand in the private market
HOSWAGE	Wage index for hospital workers in the hospital's county	Increases hospital costs
BEDS	Number of set-up beds available for use in the hospital	Increases a hospital's ability to price competitively in the private market
WORSE	Binary variable indicating that hospital scored significantly worse than expected in acute myocardial infarction treatment, suggesting low quality	Decreases a hospital's ability to attract demand in the private market
FPCHAIN	Indicator variable =1 if hospital is affiliated with a for-profit hospital chain	Increases hospital market power and strategic position
NPCHAIN	Indicator variable =1 if hospital is affiliated with a secular nonprofit hospital chain	Increases hospital market power and strategic position
RCHAIN	Indicator variable =1 if hospital is affiliated with a religious nonprofit hospital chain	Increases hospital market power and strategic position
LOOSE	Number of loosely structured vertical agreements with physician groups	Increases hospital market power and strategic position but increases costs
TIGHT	Number of tightly structured vertical agreements with physician groups	Increases hospital market power and strategic position but decreases costs
CENTSHARE	Hospital's share of net patient revenue in its HFPA	Increases hospital market power and strategic position
HHI (HERF97)	Herfindahl index of net patient revenue for the HFPA	Increases hospital market power and strategic position
MANGCARE	Share of the HFPA's discharges in non-Kaiser prepaid health plans	Decreases hospital market power
KAISER SHARE	Share of the HFPA's discharges in Kaiser HMO plans	Control variable for missing market segment
POPDEN	Population density in the hospital's HFPA	Control variable for dense market, with agglomeration economies
URBAN	Variable indicating whether the hospital is located in an urban area	Control variable for urban market, with agglomeration economies

Table 2. **Estimation Results for Hospital Pricing Interaction Model**

	OLS		Spatial Lag: k=7 closest neighbors		Spatial Lag: Inverse Distance	
	Coeff.	P-val	Coeff.	P-val	Coeff.	P-val
PPS PRESSURE	-518.467	0.087	-406.384	0.160	-493.590	0.089
LOSSES/EXPEND	831.709	0.005	806.393	0.004	804.823	0.005
SCOPE	377.621	0.110	325.240	0.150	321.714	0.156
CASEMIX	636.238	0.002	612.092	0.002	620.056	0.002
DLEVEL	0.020	0.000	0.021	0.000	0.020	0.000
CENTSHARE	243.354	0.229	235.132	0.225	241.141	0.215
HHI (HERF97)	**335.116**	**0.014**	**284.210**	**0.030**	**302.134**	**0.022**
MANGCARE	-604.385	0.081	-507.779	0.126	-503.842	0.132
KAISER SHARE	-54.084	0.880	-89.748	0.794	-70.707	0.838
FPCHAIN	-9.906	0.915	-9.790	0.912	-12.597	0.887
NPCHAIN	63.098	0.532	43.682	0.652	46.398	0.633
RCHAIN	-65.601	0.530	-74.415	0.457	-88.256	0.381
HOSWAGE	-128.021	0.711	-237.631	0.478	-232.216	0.493
BEDS	-0.698	0.038	-0.579	0.073	-0.608	0.061
LOOSE	136.795	0.022	141.514	0.013	138.066	0.016
TIGHT	-38.040	0.378	-44.806	0.279	-41.868	0.314
WORSE	-222.138	0.017	-223.531	0.012	-218.250	0.015
POPDEN	0.009	0.407	0.008	0.436	0.009	0.364
URBAN	-194.069	0.045	-181.737	0.053	-152.290	0.118
SPATIAL LAG (ρ)			0.231	0.006	0.278	0.046
N	336		336		336	
R-SQ	0.320		0.327		0.325	
Likelihood	-2599.87		-2596.83		-2598.02	
LR Test Stat p-val	*restricted model		$0.01 < p < 0.025$		$0.05 < p < 0.10$	
Global Multiplier	NA		1.300		1.295	
Full Effect, HHI			**369.47**		**391.26**	

Table 3: Sample Statistics

Variable Name	mean	standard deviation
PRICE	1534.97	673.73
PPS PRESSURE	0.28	0.13
LOSSES/EXPEND	0.03	0.12
SCOPE	0.74	0.19
CASEMIX	1.39	0.24
DLEVEL	32902.00	12591.00
HOSWAGE	1.22	0.14
BEDS	192.52	143.25
WORSE	0.15	0.36
FPCHAIN	0.17	0.38
NPCHAIN	0.15	0.36
RCHAIN	0.13	0.34
LOOSE	0.53	0.70
TIGHT	0.60	0.98
CENTSHARE	-0.12	0.18
HHI	0.47	0.28
MANGCARE	0.25	0.12
KAISER SHARE	0.07	0.11
POPDEN	3022.30	3845.40
URBAN	0.67	0.47

Table 4: Diagnostic Tests to Distinguish Empirically Between Spatial Lag and Spatial Error Processes, Using Different Specifications of Spatial Weights

k=5 neighbors	RS_{λ}	LM (error)	0.046
	$RS_{\lambda*}$	Robust LM (error)	0.630
	RS_{ρ}	LM (lag)	0.013
	$RS_{\rho*}$	Robust LM (lag)	0.120
k=6 neighbors	RS_{λ}	LM (error)	0.052
	$RS_{\lambda*}$	Robust LM (error)	0.514
	RS_{ρ}	LM (lag)	0.012
	$RS_{\rho*}$	Robust LM (lag)	0.088
k=7 neighbors	RS_{λ}	LM (error)	0.060
	$RS_{\lambda*}$	Robust LM (error)	0.363
	RS_{ρ}	LM (lag)	0.009
	$RS_{\rho*}$	Robust LM (lag)	0.044
k=8 neighbors	RS_{λ}	LM (error)	0.133
	$RS_{\lambda*}$	Robust LM (error)	0.328
	RS_{ρ}	LM (lag)	0.025
	$RS_{\rho*}$	Robust LM (lag)	0.055
Binary distance	RS_{λ}	LM (error)	0.733
	$RS_{\lambda*}$	Robust LM (error)	0.161
	RS_{ρ}	LM (lag)	0.024
	$RS_{\rho*}$	Robust LM (lag)	0.009
Inverse distance	RS_{λ}	LM (error)	0.247
	$RS_{\lambda*}$	Robust LM (error)	0.102
	RS_{ρ}	LM (lag)	0.011
	$RS_{\rho*}$	Robust LM (lag)	0.005

Methodology for Proper Diagnosis of Error Process (Anselin and Bera, 1998, p. 279)

If neither $\mathbf{RS}_{\rho}$ nor $\mathbf{RS}_{\lambda}$ are significant, but robust tests ($\mathbf{RS}_{\rho*}$ $\mathbf{RS}_{\lambda*}$) are, then ignore the robust tests.

When $\mathbf{RS}_{\rho}$ is more significant (lower p-value) than $\mathbf{RS}_{\lambda}$, and $\mathbf{RS}_{\rho*}$ is significant while $\mathbf{RS}_{\lambda*}$ is not, then lag autocorrelation is most likely the correct error structure.

When $\mathbf{RS}_{\lambda}$ is more significant (lower p-value) than $\mathbf{RS}_{\rho}$, and $\mathbf{RS}_{\lambda*}$ is significant while $\mathbf{RS}_{\rho*}$ is not, then error autocorrelation is most likely the correct error structure.

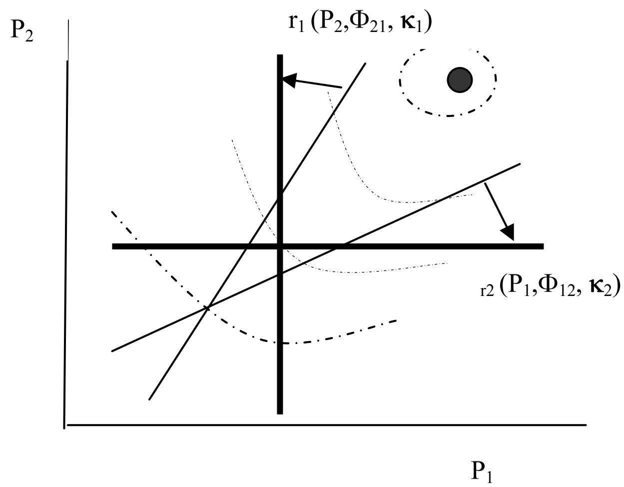

Figure 1 (Two-firm case): change in slope of reaction functions as products become worse substitutes, resulting in higher equilibrium prices for both firms. In the limit (i.e. perfectly heterogeneous products) the reaction functions are perpendicular, intersecting at a higher price than the case when there was some substitution possible, even in the absence of concerted action. This might happen if there was a substantial time-travel component to the firm's perceived elasticity of demand, and the price of oil climbed so high that people were unwilling to use any but the most local hospital. Dashed lines are iso-profit contours, which reach a maximum at the black dot in the upper right, representing the highest possible prices that could be sustained by perfectly colluding firms.

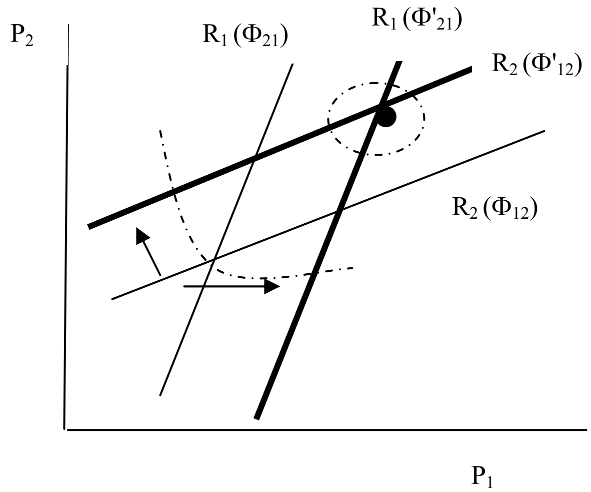

Figure 2 (Two-firm case): outward shift in reaction functions (at each price set by rival, firm now sets higher own-price) with increased 'awareness of interdependence', i.e. more concerted action (parameterized as an increase in Φ). This results in a higher price in equilibrium (Φ'> Φ). Dashed lines are iso-profit contours, which reach a maximum at the black dot in the upper right portion of the picture. This represents the highest possible prices that could be sustained by perfectly colluding firms. With perfect coordination, the curves shift out far enough that the resulting equilibrium prices are the cartel level prices, associated with the highest industry profit possible (black dot).

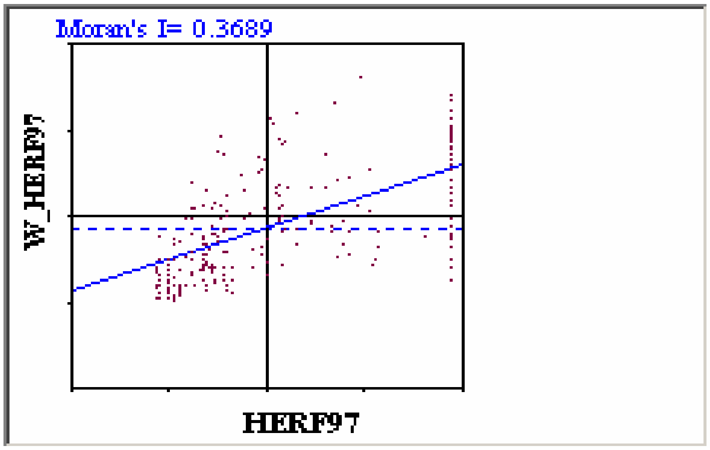

Figure 3: Moran's I plot for the spatial relationship between the raw Herfindahl (HERF97) and its spatially lagged value (W_HERF97), using K=7 closest neighbors in calculating the average HERF97 for neighbors. Small values of the Moran's I statistic (near zero) are consistent with having no spatial autocorrelation in the data. A Moran's I value near 1 indicates near perfect spatial autocorrelation.