What does Willingness-to-Pay reveal about hospital market power in merger cases? †

Gary M. Fournier [a,*] and Yunwei Gai [b]

[a] *Department of Economics, Florida State University, Tel (850) 644-5001*

[b] *Department of Economics, Florida State University, Tel (850) 644-7073*

.

April 11, 2007

Abstract

In hospital merger cases, the courts have often based geographic market areas on patient flow criteria. Given patient heterogeneity and the importance of distance to hospitals and health plan restrictions on hospital choices, Capps et al. (2003a) show that potential market power effects can be understated. While willingness-to-pay(WTP) measures derived from logit demand models provide an alternative approach, for antitrust purposes it is necessary to show how WTP relates to the likely price effects of mergers. This paper examines the connection between health plan prices and WTP that results from bargaining between managed care plans and hospitals. We study two merger cases in Florida and New York State to evaluate the reliability of this measure. Employing data available before a merger has occurred, we find that this method can provide reliable predictions of patients' post-merger willingness-to-pay that imply conservative predictions of post-merger prices.

Key words: Hospital Mergers, Geographic Market Delineation, Patient Choice, Willingness-To-Pay, Conditional Logit

JEL Classification: L40, I11, I18

---

†We wish to thank Farasat Bokhari, Paul Beaumont, Cory Capps, Marty Gaynor, Richard Lindrooth, Tommy Staahl Gabrielsen, Susan Lee, Thomas Zuehlke as well as seminar participants at the Federal Trade Commission, Charles River Associates, and the Medical University of South Carolina for comments. Please do not cite without permission from authors.

*Corresponding author (Fax (850) 644-4535)

Email addresses: gfournie@coss.fsu.edu (Gary M. Fournier), yyg1175@garnet.acns.fsu.edu (Yunwei Gai).

What does Willingness-to-Pay reveal about Hospital Market Power in Merger Cases?

Abstract

In hospital merger cases, the courts have often based geographic market areas on patient flow criteria. Given patient heterogeneity and the importance of distance to hospitals and health plan restrictions on hospital choices, Capps et al. (2003a) show that potential market power effects can be understated. While willingness-to-pay(WTP) measures derived from logit demand models provide an alternative approach, for antitrust purposes it is necessary to show how WTP relates to the likely price effects of mergers. This paper examines the connection between health plan prices and WTP that results from bargaining between managed care plans and hospitals. We study two merger cases in Florida and New York State to evaluate the reliability of this measure. Employing data available before a merger has occurred, we find that this method can provide reliable predictions of patients' post-merger willingness-to-pay that imply conservative predictions of post-merger prices.

1. Introduction

The hospital market experienced a surge in mergers and consolidations during the 1990s. Over 45% of U.S. hospitals were involved in mergers between 1990 and 1998 (Jaspen, 1998). During this period, courts often accepted the Elzinga/Hogarty (E/H) patient flow criteria to define the relevant hospital geographic market area. This method defines a relevant market as a region in which most of the residents (usually 80% or above) in this area receive hospital care within this area, and most of the patients in hospitals within this area are local residents.[1] In doing so, the courts agreed with the defendant's claims of a relatively large market area, and this ruling may have played a significant role in the loss of cases by Federal Trade Commission (FTC) and the Department of Justice (DOJ).[2]

This paper evaluates the willingness-to-pay (WTP) methodology proposed in Capps et al. (2003a), Town and Vistnes (2001), and Capps et al. (2001).[3] Compared to previous methods, this methodology considers the merger's impact from micro-data on patient choices of hospital care, thus affording a richer recognition of the relevant impacts across heterogeneous patients and local areas much smaller than typical antitrust markets. Based on patients' preferences revealed by their actual choice behavior, we can evaluate consumer welfare effects by how much more patients are willing to pay to include the merged hospitals in their choice set, and by inference, the effect of the merger on the bargaining position of hospitals compared to managed care organizations.[4]

The application of this methodology to health economics is a rather recent development.[5] It has not been established how well an empirical model based on this approach performs in predicting post-merger impacts on prices or even whether it might be a useful tool in merger analysis. Because merger challenges must be decided beforehand, it is worthwhile to consider the predictive properties of this approach under the constraints present in investigations limited by pre-merger data. We use

[1]Details on E/H criteria are in Elzinga and Hogarty (1972) and Elzinga and Hogarty (1974). There is also a debate, ignored here, on whether it is correct to confine the hospital product market to only acute inpatient care (Sacher and Silvia, 1998).

[2]Since 1984, the FTC and DOJ have lost all eleven suits that were filed to block proposed hospital mergers. Specific cases are outlined in summary testimony by Capps, Dranove, Greenstein and Satterthwaite (2003b)

[3]Gaynor and Vogt (2003) and Kessler and McClellan (1999) employ alternative structural models.

[4]For example, in the US vs. Evanston Northwestern Healthcare, the FTC official argued that managed health care plans no longer could negotiate lower prices after the merger by selectively contracting with either Evanston Northwestern or Highland Park Hospital. The merged system allegedly exploited its bargaining position to negotiate higher prices worth millions of dollars (Guerin-Calvert et al., 2005).

[5]The idea itself is not new. McFadden (1994) used the WTP to evaluate the value of preserving wilderness areas in western United States. Green et al. (1995) compared this method with Contingent Valuation using an experiment on paying for public goods. McFadden (1998) used similar method to measure the public's willingness-to-pay for public transportation improvement.

patient discharge and other publicly-provided data to investigate, with hindsight, the reliability of this methodology in case studies from Florida and New York.

This paper addresses a number of policy and econometric issues. Section 2 examines the relevance for antitrust of willingness-to-pay measures and shows how changes in this measure relate to changes in insurance prices that result from Nash bargaining between health plans and hospitals. In Section 3, we estimate models using this methodology in the context of two hospital merger cases, the 1995 merger of four hospitals in Palm Beach County, Florida and the Long Island Jewish Medical Center case in 1997.[6] The key results concern out-of-sample predictions. We imagine a pre-merger investigation that incorporates inferences about the merger's effects from data that are available *ex ante*. We examine the empirical properties of models using the WTP method for these mergers. With hindsight, for these mergers we are able to predict post-merger WTP for the merged hospitals using pre-merger data, and compare it with results from post-merger data. We find that the model yields predictions that are fairly close to post-merger outcomes. It is thus worth considering whether these models are reliable enough to justify incorporating them in merger investigations under the *ex ante* data constraints.

[6] 983 F.Supp. 121. United States v. Long Island Jewish Medical Center, E.D. NY.

2. Bargaining between MCO and Hospitals

The analysis of pricing in hospital markets must recognize the unique role of intermediation by payers on behalf of patients. Capps et al. (2003a) model the hospital market as an 'option demand' market in which managed care organizations (MCO) negotiate with hospitals for contracts to provide care on behalf of customer/members.[7] Contracts determine what local hospitals are included in the network and the payment obligations of the plan. Consumers (or employers as their representative) then choose which network to join.

While the consumers' hospital choices may be restricted by the network, prices play little or no part in the choices made when episodes requiring hospital care arise. Members of the MCO plans, after paying the premium, face no variation in out-of-pocket prices as long as they go to a network hospital. Patients choose hospitals based upon non-price characteristics of the hospital including distance, services offered, and ownership (Town and Vistnes (2001)). With empirical parameters estimated from a multinomial demand model, one can calculate patients' willingness-to-pay (WTP) for access to hospitals in the network.

The separation of consumption choices from the payments or fees for service in this market does not remove potential concerns about market power effects resulting from mergers. In antitrust law, hospital merger analysis remains focused on the effects on prices. The usefulness of WTP measures for antitrust analysis requires some understanding of how hospital 'prices' relate patients' WTP and how hospital mergers may affect prices in this model.

2.1. **MCO-Hospital negotiation.** Assume that a local market has three hospitals present and consider the bargaining with a given MCO. The behavior of the MCO, constrained by other local health plan competitors, is assumed to maximize the utility of its enrollees and ignore any costs of MCO operations.[8] The MCO negotiates individually with the three hospitals over payments and it may choose whether to include them in the network. Moreover, we assume that hospitals have a simple cost structure with constant returns to scale. The indirect utility individual i gets from going to hospital j is:

$$U_{ij} = y_i - p + a_{ij} + \varepsilon_{ij} \tag{1}$$

[7]The model in this section is adapted from Capps et al. (2003a), Capps et al. (2001) and McFadden (1998).

[8]In their appendix, Capps et al. (2003a) show that when MCOs face a competitive environment, firms seeking a contract to cover health insurance for its employees would lead MCOs to choose a network that maximizes the surplus of plan members. We are ruling out non-competitive HMO markets. Moreover, we are not allowing the possibility that hospitals might use MCOs to their bargaining advantage.

where y_i is individual i's income. The payment p is the average payment reimbursed to hospitals per member, or, equivalently the premium paid by enrollees. The payment p is assumed to be actuarially fair and to be adequate to cover the cost of hospital services in the network. a_{ij} is a vector of hospital j's characteristics, including its ownership, teaching status, nursing and capital (or equipment) intensity, services offered by hospital j, the travel time from patient i's home to hospital j, the patient's socioeconomic characteristics and the disease severity.

Under the assumption that ε_{ij} and ε_{ik} are independently-distributed, extreme value random variables, the probability that patient i chooses hospital j, given the hospital network G is:

$$s_{ij}(G, a_{ij}) = \frac{\exp(a_{ij})}{\sum_{k \in G} \exp(a_{ik})} \tag{2}$$

The MCO's objective is to maximize its enrollees' total expected utility by choosing the configuration of the network, given p. It can be shown to satisfy:[9]

$$\max_G \left(\sum_{i=1}^{N} E \max_{j \in G} [y_i - p + a_{ij} + \varepsilon_{ij}] \right) = \max_G \left(\sum_{i=1}^{N} \ln \sum_{j \in G} \exp(y_i - p + a_{ij}) \right) \tag{3}$$

For example, with three available hospitals and two already in the network, the MCO can negotiate to include the third hospital in the network if additional costs are less than its additional benefit to the enrollees:

$$\sum_{i=1}^{N} (\ln(\sum_{p,G} \exp(y_i - p + a_{ij}))) > \sum_{i=1}^{N} (\ln(\sum_{p',G'} \exp(y_i - p' + a_{ij}))) \tag{4}$$

Where $G = (1, 2, 3), G' = (1, 2)$.This inequality can be simplified to:

$$N * (p - p') < \sum_{i=1}^{N} [\ln(\exp(a_{i1}) + \exp(a_{i2}) + \exp(a_{i3})) - \ln(\exp(a_{i1}) + \exp(a_{i2}))] = WTP_3(G)$$

The term on the right side of the inequality condition is the willingness-to-pay for hospital j, measuring the *incremental* contribution of hospital j in network G to the aggregate patients' utility. Specifically, it measures the change in the maximum utility[10], summed over all patients, when hospital j is added to the network, given that the remaining hospitals in G are already present. We denote $WTP_j(G)$ the WTP of hospital j for all N enrollees in network G and $WTP_{jk}(G)$ the

[9] This result is a property of the standard extreme value distribution, ignoring the Euler's constant(-.57722) which does not affect the maximization problem. See e.g.Haab and McConnell (2003) and McFadden (1997).

[10] Alternatively, it is the prospective change in the maximum expected utility, based on the probability distribution of illness or injury events and before the patient's medical conditions are known.

joint WTP of hospital j and k in network G, i.e. the additional utility hospitals j and k together bring to the network:[11]

$$
\begin{aligned}
WTP_j(G) &= \sum_{i=1}^{N} \ln\left[\frac{1}{1 - s_{ij}(G, a_{ij})}\right] \\
WTP_{jk}(G) &= \sum_{i=1}^{N} \ln\left[\frac{1}{1 - s_{ij}(G, a_{ij}) - s_{ik}(G, a_{ik})}\right]
\end{aligned}
\tag{5}
$$

We now turn to how the rates, p, are determined under the MCO contract. Imagine a bilateral negotiation between the MCO and each of three hospitals and evaluate the Nash bargaining solutions. The Nash bargaining model is appealing for many reasons. First, the cooperative solution concept does not exclude the effect of competition among hospitals. As number of available hospitals in the market grows, the WTP for any given hospital will be reduced, leading to lower payments from the MCO. Second, the Nash bargaining model abstracts from transaction costs, assumes that negotiations involving any efficient contract will succeed, and produces a contract where the surplus from trading would be split evenly between parties. While the even split feature of the model may understate the bargaining power of either MCOs or hospitals, it is a well recognized solution.[12]

We examine the case where MCOs and hospitals negotiate over per-unit prices that the hospital receives as reimbursement for services.[13] We assume that if hospital j is excluded from the network, it can earn Π_{0j} from other sources. If it is included, however, hospital j can earn $\Pi_{1j} = p_j * Q_j - c_j * Q_j + \Pi_{0j}$. Q_j is the number of patients served and is determined *ex post* by the logit demand model of hospital choice. In general, Q_j will depend on the number and characteristics of other hospitals in the network.

[11] For details refer to Capps et al. (2003a).

[12] While a variety of bargaining situations might be appropriate, Binmore et al. (1986) establishes the linkage between the Nash bargaining solution and sequential strategic approaches. Studies in health economics including Ellison and Snyder (2001)and Gal-Or (1999) also use the Nash Bargaining Solution to model the negotiation between suppliers and buyers.

[13] This formulation comes close to the practice of negotiating deductions from gross charges, commonly attributed to MCOs. It can be shown that similar conclusions follow when capitation payments per MCO member are negotiated.

Nash bargaining between the MCO and the first hospital, hospital 1 solves the following:

$$\max_{p_1}(\Pi_{11} - \Pi_{01})(\sum_{i=1}^{N} \ln[\sum_{j=1}^{3} \exp(y_i - N^{-1}(p_1 Q_1 + p_2 Q_2 + p_3 Q_3) + a_{ij})] \tag{6}$$

$$- \sum_{i=1}^{N} \ln[\sum_{k=2}^{3} \exp(y_i - N^{-1}(p_2 Q_2' + p_3 Q_3') + a_{ik})])$$

$$\Rightarrow \max(p_1 * Q_1 - C_1 * Q_1)(-p_1 Q_1 + p_2(Q_2' - Q_2) + p_3(Q_3' - Q_3) + WTP_1(G))$$

where Q_j are the number of patients who choose hospital j in the three hospital network, while Q_2' and Q_3' are the patient volumes of hospital 2 and 3, respectively, when the contract with hospital 1 fails. The maximization problems yield three equations in prices:

$$p_1 = \frac{1}{2 * Q_1}(WTP_1(G) + p_2(Q_2' - Q_2) + p_3(Q_3' - Q_3) + c_1 * Q_1) \tag{7}$$

$$p_2 = \frac{1}{2 * Q_2}(WTP_2(G) + p_1(Q_1' - Q_1) + p_3(Q_3' - Q_3) + c_2 * Q_2)$$

$$p_3 = \frac{1}{2 * Q_3}(WTP_3(G) + p_1(Q_1' - Q_1) + p_2(Q_2' - Q_2) + c_3 * Q_3)$$

In the symmetric case where all hospitals are identical, $a_{i1} = a_{i2} = a_{i3} = a_i$, $c_1 = c_2 = c_3 = c$ and $Q_1 = Q_2 = Q_3 = Q$, the solution to the system of equations is:

$$p_1 = p_2 = p_3 = \frac{WTP_j}{Q} + c = 3\ln(\frac{3}{2}) + c. \tag{8}$$

where WTP_j is the willingness to pay for any one hospital. The solution thus shows that each hospital extracts its WTP and earns profits $\Pi = N\ln(\frac{3}{2}) + \Pi_{0j}$. When the number of hospital is J, it can be shown that in a symmetric case, $p = J\ln(\frac{J}{J-1}) + c$. As the number of hospitals increases, hospital prices approach equality with marginal cost c.

When hospital 1 and 2 merge and negotiate jointly with the MCO. The Nash bargaining solution between the merged hospitals and MCO involves:

$$\max_{p_1,p_2}(p_1 * Q_1 - C_1 * Q_1 + p_2 * Q_2 - C_2 * Q_2)(-p_1 Q_1 - p_2 Q_2 + p_3(Q_1 + Q_2) + WTP_{12}(G)) \tag{9}$$

For hospital 3, the bargaining problem is:

$$\max_{p_3}(p_3 * Q_3 - C_3 * Q_3)(-p_3 Q_3 + p_1(Q_1' - Q_1) + p_2(Q_2' - Q_2) + WTP_3(G)) \tag{10}$$

These maximization problems yield two equations in prices:

$$p_1Q_1 + p_2Q_2 = \frac{1}{2}(WTP_{12}(G) + p_3(Q_1 + Q_2) + c_1 * Q_1 + c_2 * Q_2) \tag{11}$$
$$p_3 = \frac{1}{2 * Q_3}(WTP_3(G) + p_1(Q_1' - Q_1) + p_2(Q_2' - Q_2) + c_3 * Q_3)$$

Assume again the symmetric case, where $a_{i1} = a_{i2} = a_{i3} = a_i$, $c_1 = c_2 = c_3 = c$, and $Q_1 = Q_2 = Q_3 = Q$. The solution to the system of equations is:

$$p_1 = p_2 = \frac{WTP_3(G)}{3Q} + \frac{WTP_{12}(G)}{3Q} + c \tag{12}$$
$$p_3 = 2\frac{WTP_3(G)}{3Q} + \frac{1}{2}\frac{WTP_{12}(G)}{3Q} + c$$

This solution may be interpreted in terms of the impact on the cost of the insurance plan. The insurance payment that is required from each MCO enrollee to meet all expenses with these reimbursement rates is equal to:

$$\begin{aligned}\overline{p} &= \frac{p_1Q_1 + p_2Q_2 + p_3Q_3}{N} \\ &= \frac{4}{3}\frac{WTP_3(G)}{3Q} + \frac{5}{6}\frac{WTP_{12}(G)}{3Q} + c.\end{aligned} \tag{13}$$

Compared to the pre-merger cost of insurance $p = \frac{WTP_j(G)}{Q} + c$, the hospitals receive higher payments that depend on $\Delta WTP_{12}(G)$ of the combined hospitals:

$$\overline{p} - p = \frac{5}{18Q}(\Delta WTP_{12}(G)) = \frac{5}{6}\ln(\frac{4}{3}) \tag{14}$$

where $\Delta WTP_{12}(G) = WTP_{12}(G) - (WTP_1(G) + WTP_2(G))$.

For antitrust purposes, equation 14 has important implications. It suggests that the WTP captures a key leverage factor in the negotiation between MCO and hospitals. Costs of insurance mirror the changes in the bargaining strength of the merged hospitals. After merger, however, the relevant WTP is higher because $WTP_{12}(G) > (WTP_1(G) + WTP_2(G))$

Thus, mergers that effect large changes in WTP may result in corresponding increase in the rates paid to hospitals for patient care that should raise valid antitrust concerns about harm to consumers. The value of this measure is that it imputes effects that can vary considerably by the geographic location of the MCO members. These effects may be overlooked when confining attention to fixed sets of competitors in the market.

An important limitation of the model is its neglect of alternative hospitals that might serve as a replacement. Under certain conditions, the MCO could replace the hospital demanding a higher price with one outside the network. Suppose, in our example, there is a fourth hospital with the same attributes as the three (i.e. $a_{i4} = a_{i1}$), but with higher costs ($c_4 > c$). Pre-merger, it is not worthwhile to include it in the network when this hospital's cost is larger than its additional benefit to the network.[14] When the MCO disagrees with the merged hospitals post-merger, the MCO will be better off adding the fourth hospital to the network if the inclusion cost is less than its additional benefit $N * \ln(2)$.[15] Provided that $\ln(4/3) < c_4 < \ln(2)$, the fourth hospital will not be included in the pre-merger network; while post-merger, it could be included in the network in the scenario of disagreement. $\Delta WTP_{12}(G)$ will be smaller if the MCO can use this outside hospital as a replacement for the merged hospital system. In section 3 we show that incorporating the likely replacement hospitals has only modest effects on our empirical results.

[14] The additional benefit for the fourth hospital is the WTP for this hospital with the three hospitals already in the network, i.e. $WTP_4(G = (1, 2, 3, 4)) = \sum_{i=1}^{N} \ln \sum_{j=1}^{4} \exp(a_{ij}) - \sum_{i=1}^{N} \ln \sum_{k=1}^{3} \exp(a_{ik}) = N \ln(4/3)$.

[15] Here the additional benefit is $WTP_4(G = 3, 4) = \sum_{i=1}^{N} \ln \sum_{j=3}^{4} \exp(a_{ij}) - \sum_{i=1}^{N} \ln(\exp(a_{i3})) = N * \ln(2)$

3. Empirical Analysis of Mergers in Palm Beach County, FL and Long Island, NY

We approach the empirical testing by selecting mergers that were likely to reflect significant changes in a local hospital market, and for which enough time had elapsed to allow a retrospective analysis. In 1994, Columbia announced the acquisition of HealthTrust. By that time, Columbia operated 195 hospitals and HealthTrust operated 116 hospitals nationwide. The combined company had more than $15 billion in sales, with hospitals in 37 states (Lutz and Pallarito (1995)).[16] In April 1995, when Columbia/HCA Healthcare and HealthTrust announced the completion of the merger for those units located in Florida, it had 17 hospitals in South Florida. Shortly after, in July 1995 Columbia/HCA acquired 369-bed JFK Medical Center in a nearby town of Atlantis.

We selected these Florida mergers for evaluation because of their size and other reasons.[17] The two acquisitions gave Columbia/HCA control of four hospitals in Palm Beach county.[18] Interestingly, one month after the JFK transaction, Columbia closed JFK Medical Center's long-time rival Palm Beach Regional Hospital in Lake Worth. Finally, from the standpoint of empirical evaluation, a convenient feature of the Florida mergers is that they were completed within a very short time period in 1995, thus facilitating a comparison of pre- and post-merger results.

We also analyze the 1997 merger between Long Island Jewish Medical Center and North Shore University Hospital in New York. This case clearly illustrates the importance of heterogeneity in the patient choice sets within geographic market areas as they are typically defined in hospital merger cases. Before the merger, in 1995, Long Island Jewish Medical Center had 591 beds in service and total assets of $386 million. It was a prestigious teaching hospital serving residents in Queens County and Nassau County. Three miles away was North Shore University Hospital, a 729-bed prestigious teaching hospital, also serving residents in Queens and Nassau County (Pallarito (1997)).

The DOJ, in its *Complaint* filed in District Court, focused mainly on the two hospitals' function as *anchor* hospitals.[19] Both are prestigious teaching hospitals offering a wide range of high

[16] Their hospital systems overlapped broadly in Texas, Florida, Tennessee and Utah. The FTC raised serious concerns on the issue of market power after mergers. To win approval from the agency, the company was required to divest three hospitals in Utah, two hospitals in Florida, and one hospital in both Louisiana and Texas.

[17] Hospital officials said the JFK transaction was the single largest hospital sale to an investor-owned system since the 1984 sale of Wesley Medical Center in Wichita, Kansas, to Hospital Corporation of America for $265 million. (Lutz (1994)).

[18] Before the merger, Columbia Hospital in West Palm Beach was controlled by Columbia/HCA; Palms West in Loxahatchee and Palm Beach Regional near Lake Worth were controlled by HealthTrust; and JFK Medical Center, less than three miles away, was an independent hospital.

[19] 983 F.Supp. 121. United States v. Long Island Jewish Medical Center, E.D. NY June 11, 1997.

quality services. Residents in Queens and Nassau County all wanted to have at least one of the hospitals in their insurance network. Although there were many other hospitals in this area, none of them had the capacity to substitute as an anchor hospital. Including one of the anchor hospitals in the network signified the quality of the insurance and was essential for the insurance plan's marketability. Thus, the merger would prevent the insurance company's ability to substitute one anchor hospital for the other and limit their ability to negotiate separately with the two hospitals for lower prices. DOJ contended that the merger would force insurance rates to increase by 20% (McQuiston (1997)). Respondents argued that the merger was motivated by efficiency gains and it would be infeasible for the two merged hospitals to significantly increase their market power because they were in a wide geographic market consisting of 42 other hospitals in four counties, including Manhattan (Bellandi (1997)).

In the following sections, we describe the sampling methods used to select hospitals and patients, identify the variables used in the analysis, and report the empirical findings for the Palm Beach and the Long Island merger.

3.1. **Data Sample and Variables for the Palm Beach Merger.** Data for this study are taken from public use sources in Florida that contain financial measures for short-term acute care hospitals as well as patient discharge records covering all inpatient hospital stays. The sampling methods used to select hospitals and patients in Florida yield a market area that includes the 15 acute care hospitals in Palm Beach County, plus 5 other hospitals in neighboring counties that served less than 2 percent of the total patients. To get this result, it must be noted at the outset that the sampling design was subject to certain considerations. Consistent with patient flows analysis, the service area should be self-contained for each hospital under study. This means, first, that the analysis should not overlook any other "outside" hospitals where evidence reveals that patients in the local area are able to choose, and sometimes actually choose, for hospital care. These outside hospitals are a source of competition for the hospitals involved in the merger. Second, the data set should include substantially all of the patients that received services from hospitals involved in the mergers, without restricting those patients by how far away they reside from the hospital.

Unlike the patient flows approach, however, we construct diverse zip-code level choice sets. Varying the hospital choices by small areas allows for considerable heterogeneity across the total service areas of any given hospital.

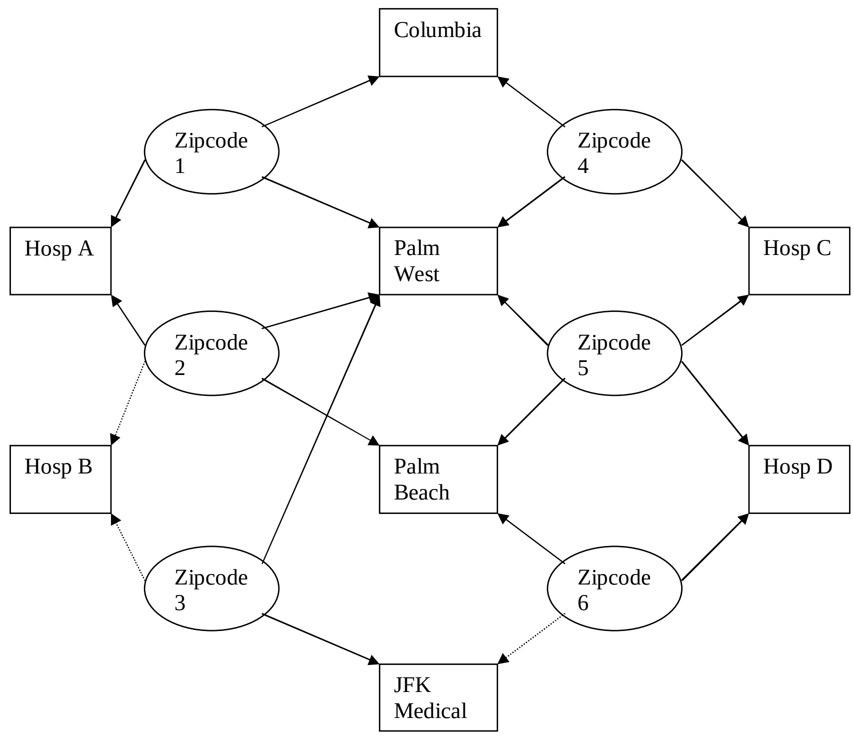

FIGURE 1. Hospital market area for the Palm Beach merger sample

Begin with a sample containing, with only minor exceptions, a complete set of observations on all patients discharged from the four hospitals involved in the mergers. Figure 1 illustrates, in principle, how the market is defined in our study. The four boxes in the middle represent the four hospitals involved in the mergers. First, identify all the zip codes for the patients who were discharged from these four hospitals. In this example, patients from zip code $1, 2, 3, 4, 5$ and 6 received care at the four hospitals. Then, looking at each zip code, the choice set includes all hospitals that draw patients from these locations. In the figure, patients from the 6 zip codes also visited hospital A, B, C and D. In the Florida data, there are 16 other hospitals whose service areas overlap our 4 focal hospitals, however, the percent of the hospitals' total discharges included in the sample, i.e. the hospital coverage rates, are low.

Some zip codes were excluded if very small numbers of patients are drawn to the four focal hospitals.[20] In the final sample, we account for 90,113 patients in total, over 92% of all patients treated in areas served by these hospitals. Thus, subject to these exclusions, the sample contains essentially all patient discharges in the areas where the four focal hospitals compete. Similar patient choice sets are constructed for the 1997 post-merger data.

[20]In a separate appendix, we discuss these sampling issues at length and explore the sensitivity of the model's predictions to changes in the sampling design.

One caveat is that we cannot identify for certain the exact choice set for each patient. For instance, if an HMO payer restricted hospital choices, while Medicare does not, we might overstate the range of choices for the former from data including the latter. However, we find that there are identical choice sets obtained by zip-code when constructed for Medicare patients and for the private payer categories. Even so, if there are more than one HMO available locally, different HMO patients could potentially face different choices and our method would identify the union of all HMO choices.

After selecting hospitals and patients in our study, we estimate the following conditional logit model with choice sets that vary by patient zip code location:

$$S_{ij}(G, X_i, \lambda_i) = \frac{a_{ij} \exp(\alpha R_j + H_j' \Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} X_i + \tau_3 T_{ij} R_j)}{\sum_{k=1}^{J} a_{ik} \exp(\alpha R_k + H_k' \Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} X_i + \tau_3 T_{ij} R_k)} \tag{15}$$

Where $a_{ij} = 0$ if choice j is not available to individual i.

where the specification of the explanatory variables closely approximates those in Capps et al. (2003a):

$H_j = [R_j, S_j]$, R_j is a vector of hospital j's characteristics, including its control types (for profit, not for profit, or government), teaching status, nursing intensity, capital intensity etc. S_j are services offered by hospital j. R_j and S_j are from hospital financial data collected by state regulators.[21]

T_{ij} is the travel time from patient i's home to hospital j. These measures of distance to the hospital are from a public source, www.mapquest.com.

X_i include detailed clinical and demographic information from the public use inpatient discharge database in Florida: diagnoses (DRG code),[22] length of stay, payer category (Medicare, HMO etc.), Charlson Index, patients' demographics (age, race, sex etc.), and patient zip code locations. Income data are taken from the Census.[23]

[21]The data is collected by the Florida Agency for Health Care Administration (AHCA) using the hospital uniform reporting system. Currently 238 Florida hospitals are required to submit fiscal year end financial reports to AHCA.

[22]Patients' diagnoses and procedures are coded based on DRG and MDC. Except for the approximately 1.8% patients in MDC 25, 20, 2, 24 and 22 that were coded as "others", the diagnoses are aggregated up to MDCs.

[23]Income from the 1990 Census was obtained from 1990 Summary Tape File 3 (STF 3) at http://www.census.gov/main/www/cen1990.html. Income from the 2000 Census, Census 2000 Summary File 3 (SF 3) - Sample Data at http://www.census.gov/main/www/cen2000.html These sources provide per capita income by zip code and race in Palm Beach County. Income in 1994, the mid year between the census years, thus can be calculated as the average of the 1989 and 1999 income after adjusting price change using the BLS' release of CPI-U-RS April 27 2005, at http://www.bls.gov/cpi/cpiurstx.htm.

To calculate the total WTP for a hospital, estimates are required of patients' conditional probability for each type of disease, the mean length of stay, the mean Charlson severity index, and the mean number of diagnoses and procedures for a given condition. Using statewide patient discharge data from 1993 to 1995, we calculated these variables separately by demographic groups defined on patients' race, income, gender and age. A summary of variables is given in table 1 and sample statistics for patient characteristics are shown in table 2.

3.2. **Empirical Results from the Palm Beach, FL Mergers.** Table 3 reports the estimation results from the sample that includes all patients insured by commercial insurance, Medicare, Medicare-HMO, commercial HMO and commercial PPO.

The estimated coefficients for the most part, are highly significant, including those associated with dummy variables for for-profit status, nursing intensity, capital intensity, and hospital services offered. As previous research has shown, the travel time to the hospital and its interaction with other terms in the model are all very significant. In general the model is successful in capturing the key features of the choice set, and is broadly consistent with the results obtained in the earlier analysis of Capps et al. (2003a).[24] Within the assumptions of the conditional logit model, we focus on out-of-sample robustness, i.e. how well the model can predict, prospectively, how much the merger will change the aggregate value of WTP for the combined hospitals.

Prior to knowing what her disease/injury status will be,[25] individual i's WTP to include hospital j in network G is computed by evaluating the potential WTP over her entire set of possible medical conditions Z. Denote $p(Z_i|y_i)$ the probability of individual i having disease Z_i conditional on her socioeconomic attributes and location. The estimated WTP can be expressed as:

$$WTP_j^i(G, a_{ij}) = \sum_z \ln \left[\frac{1}{1 - s_{ij}(G, a_{ij})} \right] p(Z_i|y_i) \tag{16}$$

[24] A few of the point estimates in our model are different from Capps et al. (2003a). The estimated coefficient on travel time to the hospital is smaller in magnitude than the earlier study (-0.068 compared to -0.2562). Moreover, the control variable for hospitals having organ transplant services increases the probability of being chosen by the patient in both papers, but the point estimate of the coefficient on this dummy variable is much larger in our paper (2.163 compared with 0.3693). The point estimates on these variables are not, however, the corresponding marginal effects because they depend on the extensive interaction terms in the model. Therefore, despite the differences, the marginal impacts may be similar.

[25] Capps et al. (2003a) refer to this prior as the *ex ante* WTP, while, after the health status is determined, the individual expresses an *ex post* WTP.

Summing over all patients who have hospital j as an alternative in their choice set gives the population's WTP for hospital j:

$$WTP_j(G) = \sum_{i=1}^{N} \sum_{z} \ln \left[\frac{1}{1 - s_{ij}(G, a_{ij})} \right] p(Z_i|y_i) \tag{17}$$

Similarly, the predicted post-merger WTP for merged hospital j and k is:

$$WTP_{jk}(G) = \sum_{i=1}^{N} \sum_{z} \ln \left[\frac{1}{1 - s_{ij}(G, a_{ij}) - s_{ik}(G, a_{ik})} \right] p(Z_i|y_i) \tag{18}$$

The willingness to pay for hospital j in equation 17 and the predicted WTP change implied by equation 18 are the main products of the model, in turn, affecting the post-merger price changes. If their measurement is imprecise, the predictions about future price changes will also be unreliable.

To evaluate the reliability of out-of-sample prediction, we predict WTP using pre-merger data, then repeat estimation on post-merger data to calculate the estimated post-merger WTP. Suppose hospital j and k merge and denote the pre-merger prediction of post-merger WTP, $\widehat{WTP}_{jk}(G)$. Next, post-merger data is used to estimate equation 15 and calculate the estimated post-merger WTP for j and k, $\widetilde{WTP}_{jk}(G)$. The difference is $\Delta WTP_{jk}(G) = \widehat{WTP}_{jk}(G) - \widetilde{WTP}_{jk}(G)$, i.e., our measure of the prediction error of the model from the two data sets pre-and post-merger. Traditional t-tests or other statistics assume either the difference would have the t-distribution or else one model is a nested version of the other. These conditions are clearly violated in our case. We resolve this problem by using bootstrap methods.[26]

The left side of table 4 reports the results obtained for $\widehat{WTP}$ from the 1994 data. The results to the right of the table summarize $\widetilde{WTP}$, based on estimated parameters from the 1997 post-merger data.[27] Bootstrap methods on 100 pseudo-samples were used to analyze the empirical distribution of the difference of the two estimated WTPs.

[26]We draw, with replacement, n pseudo samples, each with N observations from the original pre-merger data. Similarly, we create n pseudo samples from the post-merger data. The model is re-estimated for each pseudo-sample, and the repeated estimates are used to obtain $\widehat{WTP}$, as well as post-merger estimate $\widetilde{WTP}$, and take the difference.

[27]For comparisons across the two sample years, one further adjustment is necessary to account for the fact that, due to growth, the inpatient volume is different between 1994 and 1997. To accommodate this change, let $N97$ the number of patients in 1997, and $N94$ is the number in 1994, for the later year, $\widetilde{WTP}$ is multiplied by $N94/N97$ to give a scaled value. This adjustment is equivalent to assuming that there is a neutral, aggregate demand growth, which seems reasonable for the state of Florida during these years.

The mean difference between the *ex ante* predicted changes and the *ex post* estimated changes was found to be only 3.9%.[28] Thus, it would appear that this methodology can provide excellent out-of-sample prediction, and may be reliable enough for its intended use. The Palm Beach mergers are associated with substantial changes in WTP, on the order of about 20%. Further, as our earlier bargaining analysis suggests, we can infer qualitatively similar profit and price changes within small confidence intervals.

Our results can be compared with the Elzinga/Hogarty (E/H) method. Based on the patient follow criteria, the 15 hospitals in Palm Beach County constitute a relevant geographic market, and all patients are assumed to have access to the full set of hospitals.[29] Consequently, the pre-merger Herfindahl Hirschman Index, HHI is 898, while the post-merger HHI is 984, an increase of only 86 points. Under prevailing merger guidelines, the market is considered to be unconcentrated and these mergers are unlikely to have adverse competitive effects. But the mean change in WTP is 24%, and would signal the need to examine the merger more closely.

The sample used to this point includes patients who are insured under a variety of insurance plans: commercial fee-for-service, Medicare, Medicare-HMO, commercial HMO and commercial PPO arrangements. Clearly, sampling from such diverse groups of patients may introduce problems. The Medicare program reimburses hospitals on the basis of a fixed price per admission for treatment and does not bargain with individual hospitals. Reimbursement rates would not change simply because local hospitals merge.

To alleviate this problem, we use the empirical estimates to calculate the WTP for the commercial insurance, commercial HMO and PPO patient observations only. This procedure yields the estimated WTP changes limited to patients who are most directly affected by mergers. Table 5 reports the change in the estimated willingness to pay from pre-merger data to results estimated post-merger based on 100 bootstrap samples. Across the samples, the predictions for commercial insurance, HMO and PPO patients are 5.08% higher than the post-merger WTP. Thus, the model seems to be quite stable across time, providing some evidence that analysis conducted before the merger occurs may give insight about the mergers effects.

[28]In an expanded sample constructed to test robustness and reported in the appendix, the predicted WTP is 4.79% higher than the post-merger WTP.

[29]The two criteria are termed Little In From Outside (LIFO) and Little Out From Inside (LOFI). In Palm Beach County, FL, LIFO =92% and LOFI = 89%

3.3. **Empirical Results from the Long Island Merger.** We apply the same methodology to analyze the Long Island merger case.[30] Here, we report empirical results addressing the reliability of the model's out-of-sample WTP prediction, $\widehat{WTP}$, from pre-merger data.

Using data drawn from public sources,[31] we again use empirical estimates of the logit model to predict $\widehat{WTP}$, the WTP with pre-merger 1996 data.[32] Next, we use the 1999 post-merger data to re-estimate the model and use the new coefficient estimates to compute $\widetilde{WTP}$, the estimated post-merger WTP in 1999. Bootstrap methods on 100 pseudo-samples are used to analyze the empirical distribution of the difference of the two WTPs. As in the previous analysis, we first conduct the prediction using all patients in the data, i.e. patients with Medicare, Medicare HMO, Blue Cross, commercial HMO or commercial fee-for-service insurance. These results are summarized in table 6. Before the merger, the two hospitals had a combined WTP of 60310 in 1996 and the predicted post-merger WTP was 75552; that amounts to an increase of about 25% in WTP if the merger were allowed. The post-merger WTP in 1999 was 77065 after adjusting patient volume. On average, the predicted post-merger WTP is only 2% different from the predicted post-merger $\widetilde{WTP}$.

A final set of predictions were conducted using the previous strategy of predicting WTP only for observations on the commercial insurance, commercial HMO and PPO patient observations, and are reported in table 7. The predictions match the post-merger results with a 2.7% error rate. Thus, the results confirm, qualitatively, the interpretation provided from the full sample.

In sum, the analysis from the Long Island merger provides some support for the position that these choice model approaches may have good predictive accuracy. It is interesting to compare our results with the changes in HHI determined by patient flow criteria. Queens and Nassau Counties were considered by both parties as the relevant geographic market, however, the government argued that the two merging hospitals were "anchor" hospitals and competed only against each other, while the defendants argued for the inclusion of all hospitals located in the two counties. If we adopt the defendants position, LIFO = (Local Consumption from Local Supply)/(Local Consumption) = 92% and LOFI = (Local Consumption from Local Supply)/(Local Production)=81%. Based on discharges for the hospitals in these counties, the pre-merger HHI = 567.8574 and the post-merger

[30]The separate appendix discusses various sample construction issues, including the selection of hospitals and patients and other properties of the sample.

[31]Inpatient discharge data are taken from Healthcare Cost and Utilization Project (HCUP). These data include information on the variables T_ij and X_i. Hospital financial variables, H_j are collected from AHA Guide to Health Care Field and Hospital Cost Report from Center for Medicare and Medicaid Services. Summary statistics are provided in the appendix.

[32]For the sake of brevity, we omit reporting the estimated parameters from the model. These results are available upon request from the authors.

HHI = 800.8434. Under prevailing guidelines, a merger of this magnitude would be unlikely to cause adverse competitive effects in the market. In contrast, we find the price effects are likely to be substantial, indicating a change in the WTP in excess of 20%.

3.4. **Predicting price effects of mergers.** While it is significant that our *ex ante* estimated WTP is close to the *ex post* value, there could be offsetting changes between the two periods that are not specified in the model. WTP might have been affected for reasons unrelated to our interpretation, such as changes in the value of travel time. If, however, it could be shown that our model can be used to predict price changes, then our interpretation gains some credence. We turn now to an analysis of prices in Florida.[33]

In some bargaining models, as shown above, WTP is correlated with the Nash equilibrium prices in contracts with the hospital, while changes in its value induced by mergers would affect prices proportionately. To examine the price effects in the context of hospital services requires a method of constructing an overall index of prices across many diverse services and assessing the correlation between WTP and prices.

We construct a price index following Keeler, Melnick and Zwanziger (1999), Dranove and Ludwick (1999), Cuellar and Gertler (2006), Ciliberto and Dranove (2006) and Melnick and Keeler (2007). For the pre-merger data in 1993 and 1994, and using private pay patients in each of the selected DRGs,[34] we regress the log of net price per day:

$$\ln(netp/los)_{ijd} = x'_{ijd}b + \alpha_d \ln(WTP_j) + \varepsilon_{ijd} \tag{19}$$

where observations are on patient i in DRG category d at hospital j. The dependent variable, $netp/los$, is an estimate of the net price per day.[35] The explanatory variables control for length

[33] Results in this section and the one following are limited to the Florida merger due to financial data requirements.

[34] The sample includes all private pay patients in a set of DRGs selected to reflect the most common diagnoses for hospital patients in the state. Keeler et al. (1999) constructs a price index on 10 DRGs selected by Lynk (1995), that were defined as the DRGs treated by the largest number of hospitals in the state. The reason for this "most widely treated" approach was to capture patients in DRGs that could be given hospital care without specialized professionals or equipment and could be served by most community hospitals. Over time the top-10 ranked DRGs varies considerably, so for our index, we selected a new and larger set of DRGS to represent a wider array of hospital services. First, we looked at a broader set of top-50 ranked DRGs based on Keeler's "most widely treated" methodology for 1993 and 1994. While our method retains the DRGs in Keeler, we eliminated 10 DRGs that were not present in the discharge records of the four hospitals of our study, leaving 40 DRGs. In addition, we looked at a broader set of top-50 ranked DRGs, ranked by the largest discharge frequency in the state for 1993-1994. Eliminating 21 DRGs not present in the data left 29 DRGs in the second index.

[35] The net price is calculated as the gross charges for each discharge discounted by the hospital-specific ratio of revenue deduction to total gross revenue for private pay patients in the reporting period. While the actual price paid for the patient's care is not available in the data, this measure is often used to get a rough estimate of it. See, e.g., Keeler et al. (1999), Dranove and Ludwick (1999), Gaynor and Vogt (2003) and Melnick and Keeler (2007).

of stay, *los*, patient demographics (gender, race and age), discharge status, source of admission and other factors, including the log of the estimated WTP for the hospital where the patient was treated. The coefficient α_d measures the elasticity of WTP with respect to price for each DRG. Using patient frequency weights by DRGs, wt_d, a weighted average of α_d across the set of DRGs, $\widetilde{\alpha} = \sum wt_d \alpha_d$ gives our measure of the overall elasticity of prices with respect to WTP. Thus, our predicted price change from the merger would be: $\widetilde{\alpha}(\%\Delta WTP)$. Moreover, a weighted average prediction of prices would be used to obtain the price index, $P = \sum_d wt_d \exp(\ln(netp/los)_d)$.

Table 8 lists the elasticities of price with respect to WTP in two sets of selected DRGs. The overall elasticity is robust to the selection of DRGs in the price regressions. The first set of DRGs is selected using the "most widely treated" method, i.e. DRGs treated by the largest number of hospitals in the state. The second set includes DRGs with the largest discharge frequency in the state. In both sets, WTP has a positive and significant, but inelastic effect on prices. The overall elasticity (standard error) in the first set of DRGs is estimated to be 0.627 (0.032) and significant, while in the second set it is 0.683 (0.011) and significant. Recall that, from our pre-merger bootstrap analysis in Table 5, the post merger WTP was predicted to increase 20.89% on average. Combined with the overall price elasticity estimates, we predict that the merger will lead to an increase of hospital prices by 13.10% to 14.26%.

We can further compare the predicted price increase with the actual price increase: $\frac{\overline{P}-P}{P}$, where P is the pre-merger price index and $\overline{P}$ is the post-merger price index in 1997, evaluated at the patient-DRG mean characteristics in 1994. In the set of "most widely treated" DRGs, prices increase 23.13% post merger compared to our predicted price increase of 13.10%. In the set of DRGs with "largest discharge frequency", the price increase is 24.68% compared to the predicted price increase of 14.26%.

Our method gives relatively conservative estimates that, in this sample, under-predict the future price changes. That property may be desirable, however, given estimation uncertainty and the possibility of confounding changes in the local market. For instance, there may be other cost drivers such as wages or equipment that are affecting prices in the later years. Finally, the method does not account for changes associated with quality improvements or efficiency gains from the merger; these potential gains are beyond the scope of this analysis.

3.5. **Impact of alternative hospital networks in the measurement of merger effects.** A key assumption in the construction of the WTP for each hospital is that if the hospital were removed, the alternative maximum utility from the new network would be based upon the remaining hospitals. The MCO could, however, replace the hospital demanding a higher price with one outside the network if the costs of adding this hospital are less than the higher price demanded by the network hospital. This suggests that we may have over-estimated the WTP assuming the option of alternative network is not available to the MCO. In practice, the alternative state of the network, i.e. what alternative hospitals would be added to the network, is unobserved. We consider the implications of our analysis when MCOs are able to construct an alternative network by replacing the network hospitals with ones that are not included in the network before (hereafter, called the "replacement effect").

Only a few studies empirically analyzed the replacement effect because the information on MCOs hospital network configuration is confidential and the alternative state of the network is unobservable. Capps et al. (2002), Capps et al. (2003a) and Gaynor and Vogt (2003) studied the price effects of mergers without replacement, i.e. the size of the network would be reduced when the hospitals are excluded. Their hypothesis is that the MCOs have already included all local hospitals in the network; therefore, the replacement effect is unlikely to occur.[36]

An important exception is Town and Vistnes (2001). With pricing information from two major MCOs in the Los Angeles area and their hospital network configurations, Town and Vistnes (2001) analyze the incremental value of a hospital to the MCO's network. While most of the time, the MCOs dropped the hospital from the network without replacing it, evidence showed that one MCO in their study used a replacement to constrain price 21% of the time and the other 38% of the time. In this manner, MCOs may be able to limit price increase caused by increased hospital bargaining power following a merger. An appropriate adjustment to WTP reflecting replacements in the network would likely reduce the bargaining power of the hospital, whether or not a merger has occurred.

Recall that in section 3.1, we construct choice sets by assuming that all patients in a given zip code face a fixed set of alternative hospitals and we infer that set from the consumption patterns observed in the discharge data. We simulate the replacement effect by examining empirically the

[36] Capps et al. (2002) argues that the networks in San Diego area are quite inclusive, i.e. all hospitals in this area are included in the network, based on discussions with local MCO executives. Cogswell (2002) provides evidence that the MCO networks in Connecticut in 2000 consist of almost all of the hospitals in the state.

most likely replacements in the data. We identify a replacement hospital from the 16 hospitals not involved in the merger in Florida, as the one that, when added to the choice set, yields the highest contribution to the patients' joint utility.[37]

The results of our replacement analysis are shown in table 9. For hospitals involved in the merger, the first best replacement is indicated. A common feature across the replacement hospitals is that they are all very close to the merged hospitals with an average distance of 11 miles and a driving time of 17 minutes. Distance is known to be a major factor in choosing hospitals.

We predict the post-merger joint WTP for the merged hospital system using six different alternative network configurations depending on the number and combination of the three replacement hospitals (see table 10). The WTP for Palm Beach Regional Hospital decreases most from 2598.40 to 2131.36, an 18% decrease. The decrease for Palm West Hospital is 8.6%, the smallest of the four. As expected, the largest impact of replacement on the joint WTP of the merged hospital system is when we add all three replacement hospitals as a substitute for the merged system. The post-merger WTP increase is 17.33% in this case, compared to 20.88% without replacement.

In addition to its impact on the calculation of WTP, we are also interested in how replacement affects our predictions about price elasticities and the likely price changes from the merger. We repeat the price regression of equation 19 in section 3.4, adjusting the WTP measures to incorporate replacements outside the network. The overall elasticity increases only slightly from 0.627 to 0.640 for the first set of "most widely treated" DRGs, and from 0.683 to 0.691 for the set of DRGs with "largest discharge frequency". Accordingly the predicted price index increases in magnitudes ranging from 11.09% to 23.95% depending on the choice of elasticity and alternative networks.

While we cannot know for certain what replacements would be made *ex post*, the issue might be determined in the context of an ongoing merger investigation. Here we have simulated the most likely choices of replacement. One can see how well the pre-merger analysis predicts price changes under alternative assumptions. We find that the ability of the MCO to use hospitals outside the

[37] This method is similar to the study by Town and Vistnes (2001). In that study, the best substitute among hospitals outside the network is identified as the one with the highest probability of being chosen when patients are restricted to having only one replacement from the set of those outside hospitals. Our choice of replacement hospital, the one with highest WTP is also the one most likely to be chosen because $WTP_j = \ln(1/(1 - S_j))$, where S_j is the probability of choosing hospital j. One difference is that in our model the replacement hospital may already be included in some zip code choice sets but not in others, while Town and Vistnes (2001) assumes that patients face a universal choice set and the substitute hospital is not an existing alternative for any patient.

network as replacement for network hospitals decreases the bargaining power of the merged hospitals somewhat and reduces the post-merger WTP.

In the case of merged hospital systems, replacement is likely to be more effective in limiting the post-merger price increase when there are relatively more alternatives available in the local market. We find that, if the MCO can replace each affiliate of the merged hospital system with an alternative hospital, there is a further weakening of the bargaining position of the merged hospitals. For example, when the MCO replaces the whole merged system with only one hospital, the post-merger WTP is estimated to increase over 30%; in contrast, there is only a 17% increase when three replacements exist.

4. Conclusions

The value of obtaining estimates of willingness-to-pay (WTP) based on empirical analysis of demand is shown clearly in our bargaining analysis. While the structure is simplified, the results of bargaining in the option demand framework lead to a close correspondence between rates paid to hospitals and the aggregate WTP. Co-located mergers provide hospitals with extra bargaining power in contracts with MCOs and the resulting effects on prices are proportionate to the change in WTP implied by the joint ownership.

Our empirical results reveal much about the two mergers in our study. First, both mergers were likely to create a sizeable change in WTP, not because there are insufficient numbers of hospitals in the geographic areas, but because many patients residing within face a more limited set of choices than the set of all hospitals identified by the traditional methods. Second, the empirical approach, when taken prospectively to construct WTP estimates from pre-merger analysis, is reasonably accurate when compared against the results obtained from the post-merger data. The predicted changes may be judged accurate enough to suit preliminary investigations about the likely impacts of hospital mergers on local consumers in situations where choice constraints are highly localized in the affected metropolitan area.

Although the WTP estimates depend upon what is assumed about the MCO's ability to substitute replacement hospitals in the network, the predictions are fairly robust to this possibility. Finally, estimated WTP is significant in regressions on hospital prices, while post-merger price indexes, constructed as in Keeler et al. (1999) and recent studies, predict somewhat smaller impacts than actually occurred.

The Long Island merger is a particularly pertinent example of the geographic problem facing antitrust authorities. During the investigation, DOJ argued that the merger would violate the merger guidelines and significantly increase the two hospitals' joint market power. But the court ruled in favor of the merger because of the parties' not-for-profit status and the high volume of patient flows across a broad area. Our results support the DOJ's concerns about this merger. Moreover, the pre-merger prediction on WTP is about 2% for the sample of all patients (2.7% for the private pay patients) below its estimated post-merger value.

It would be constructive to find an alternative method to define hospital market that is consistent with consumer choice theory and provide a stronger foundation for merger analysis. The willingness-to-pay methodology provides a promising alternative. The patient discharge data and financial data required for this method are uniform and widely available in many states, so it should be feasible to incorporate this kind of analysis when circumstances require it. This study recommends further research concerning how well the new approach can predict the impact of a merger, and whether the prediction is reliable.

Table 1. Variables Used in the Model

Variable	Definition
Rj	NFP, FP, Gov: dummy indicating a hospital's type of control; Not-For-Profit (NFP), For-Profit (FP), Government Hospital (Gov)
	Teaching: dummy indicating whether a hospital is a teaching hospital.
	nurse_int : nursing intensity: nursing hours divided by patient days
	capital intensity: dollar value of capital asset divided by inpatient days, (include land, land improvement, buildings, fixed equipment, leasehold improvement, movable equipment, construction in progress)
	h_transplant: dummy variable for transplant services
Sj(dummy)	h_nerv:dummy variable indicating whether the hospital specializes in the disease of nervous system
	h_resp:respiratory
	h_cardio: cardiac care
	h_labor: labor and delivery
	h_mri: magnetic resonance imaging
	h_psych: psychiatric care
Xi	admission: type of admission: 1. Emergency 2. Urgent 3. Elective 4. Newborn 5. Other Male: indicating gender White: indicating race Age: patient age at admission elderly: indicating whether the patient is over 60 child: indicating whether the patient is under 17 income1994: calculated from 1990 and 2000 Census, based on zip codes and race lstay: length of stay ndx: number of other procedures npx: number of other diagnoses xchrlson: Charlson Index (instead of using pcctravel)
	cardio: dummy variable indicating whether the patient has cardio disease labor: labor and delivery resp: respiratory disease digest: disease and disorders of the digestive system muscl: disease and disorders of the musculoskeletal system and connection tissue
	nerv: diseases and disorders of the nervous system urinary: diseases and disorders of the kidney and urinary tract genital: diseases and disorders of reproductive system psych: mental diseases and disorders liver: diseases and disorders of the hepatobiliary system and pancreas
	endor: endocrine, nutritional and metabolic diseases and disorders infection: infectious and parasitic diseases integ:diseases and disorders of the skin, subcutaneous tissue and breast myelop: myeloproliferative disorders injury: injuries, poisonings and toxic effects of drugs
	ent: diseases and disorders of the ear, nose and throat image:magnetic resonance imaging other: diseases and disorders of the eye,burns, alcohol/drug use and alcohol/drug induced organic mental disorders factors influencing health status and other contacts with health services
Time	t: travel time for patient i to hospital j
Distance	travel distance between patients and hospitals
Insurance:	medicare: patient insured by Medicare medicarhm: patient insured by Medicare-HMO blue cross:patient insured by blue cross commins: patient insured by commercial insurance commhmo: patient insured by Commercial HMO commppo: Commercial PPO

Table 2. Patient Sample Statistics in Florida Merger Case in 1994 and 1997

	Premerger 1994				Postmerger 1997			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
nfp	0.597	0.491	0	1	0.424	0.494	0	1
fp	0.381	0.486	0	1	0.557	0.497	0	1
teaching	0.000	0.000	0	0	0.001	0.031	0	1
nurse_int	0.062	0.017	0.045	0.125	0.064	0.022	0.036	0.164
cap_int	0.807	0.282	0.109	1.655	0.961	0.404	0.436	1.809
h_transplant	0.002	0.045	0	1	0.001	0.031	0	1
h_resp	1.000	0.000	1	1	1.000	0.000	1	1
h_cardio	0.806	0.396	0	1	0.831	0.375	0	1
h_labor	0.664	0.472	0	1	0.652	0.476	0	1
h_mri	0.748	0.434	0	1	0.902	0.297	0	1
h_psych	0.314	0.464	0	1	0.301	0.459	0	1
admission	1.931	0.929	1	5	1.961	0.928	1	5
male	0.442	0.497	0	1	0.444	0.497	0	1
white	0.839	0.367	0	1	0.841	0.365	0	1
age	59.072	26.391	0	99	59.848	26.431	0	99
elderly	0.632	0.482	0	1	0.635	0.481	0	1
child	0.102	0.302	0	1	0.102	0.303	0	1
income	23.192	12.279	5.534	92.646	24.298	12.413	0	94.544
lstay	5.346	5.862	1	202	4.788	5.224	1	367
ndx	4.399	2.856	0	9	4.556	2.867	0	9
npx	0.773	1.482	0	9	0.769	1.473	0	9
xchrlson	2.930	2.306	0	14	2.953	2.257	0	14
cardio	0.249	0.432	0	1	0.247	0.431	0	1
labor	0.138	0.345	0	1	0.128	0.334	0	1
resp	0.098	0.298	0	1	0.104	0.305	0	1
digest	0.096	0.294	0	1	0.093	0.290	0	1
muscl	0.084	0.278	0	1	0.084	0.277	0	1
nerv	0.069	0.254	0	1	0.073	0.261	0	1
urinary	0.033	0.180	0	1	0.033	0.178	0	1
genital	0.042	0.202	0	1	0.036	0.186	0	1
psych	0.024	0.152	0	1	0.036	0.186	0	1
liver	0.027	0.162	0	1	0.026	0.160	0	1
endor	0.028	0.166	0	1	0.029	0.169	0	1
infection	0.024	0.154	0	1	0.030	0.170	0	1
integ	0.021	0.145	0	1	0.019	0.137	0	1
myelop	0.019	0.137	0	1	0.017	0.131	0	1
injury	0.010	0.100	0	1	0.009	0.094	0	1
ent	0.009	0.093	0	1	0.008	0.090	0	1
image	0.031	0.172	0	1	0.036	0.186	0	1
other	0.027	0.162	0	1	0.027	0.161	0	1
time	11.961	11.216	0	102	12.332	10.570	0	102
distance	7.482	8.275	0	75	7.706	7.812	0	75
medicare	0.472	0.499	0	1	0.411	0.492	0	1
medcarhm	0.054	0.226	0	1	0.136	0.343	0	1
commins	0.130	0.337	0	1	0.069	0.254	0	1
commhmo	0.169	0.374	0	1	0.236	0.424	0	1
commppo	0.175	0.380	0	1	0.148	0.355	0	1
N. of Obs.	63992				76455			

Note: variables are defined in table 1.

Table 3. Estimation Results from the Florida Merger Case.

Variable	Coeff.	Std. Err.	Variable	Coeff.	Std. Err.
fp	-1.094††	0.058	h_labor	-0.304††	0.017
fp*male	0.173††	0.018	h_lab*labor	6.608††	0.379
fp*white	0.225††	0.032	h_mri	-0.306††	0.019
fp*elderly	0.315††	0.045	h_mri*image	0.466††	0.065
fp*child	-0.061	0.053	h_psych	0.335††	0.018
fp*age	0.016††	0.001	h_psy*psych	3.402††	0.105
fp*income1994	0.004††	0.001	time	-0.068††	0.005
fp*lstay	0.000	0.002	t*fp	-0.003‡	0.001
fp*ndx	-0.083††	0.004	t*nurse_int93	0.906††	0.037
fp*npx	0.013‡	0.007	t*cap_int93	0.044††	0.002
fp*xchrlson	-0.070††	0.006	t*male	0.000	0.001
nurse_int93	-15.829††	1.764	t*white	-0.007††	0.002
nurse*male	-1.288‡	0.593	t*elderly	-0.013††	0.003
nurse*white	3.062††	0.982	t*child	-0.028††	0.003
nurse*elderly	-3.155‡	1.416	t*age	-0.002††	0.000
nurse*child	-3.385‡	1.530	t*income1994	-0.001††	0.000
nurse*age	-0.300††	0.034	t*lstay	0.000‡	0.000
nurse*income	0.382††	0.049	t*ndx	0.000	0.000
nurse*lstay	-0.494††	0.065	t*npx	0.007††	0.000
nurse*ndx	2.783††	0.131	t*xchrlson	0.005††	0.000
nurse*npx	-0.311	0.214	t*cardio	-0.017††	0.003
nurse*xchrlsonn	0.353†	0.193	t*labor	-0.016††	0.003
cap_int93	-0.633††	0.114	t*resp	-0.02††	0.003
cap*male	0.007	0.039	t*digest	-0.019††	0.003
cap*white	-0.481††	0.060	t*muscl	0.005	0.003
cap*elderly	-0.302††	0.089	t*nerv	-0.019††	0.004
cap*child	-0.028	0.098	t*urinary	-0.006	0.004
cap*age	0.017††	0.002	t*genital	0.012††	0.004
cap*income	0.001	0.003	t*psych	0.021††	0.006
cap*lstay	-0.013††	0.004	t*liver	-0.022††	0.004
cap*ndx	-0.003	0.009	t*endor	-0.013††	0.004
cap*npx	-0.287††	0.015	t*infection	-0.01‡	0.004
cap*xchrlson	0.090††	0.013	t*integ	-0.009†	0.005
h_transplant	2.163††	0.121	t*myelop	0.017††	0.005
h_nerv	-0.525††	0.026	t*injury	-0.008	0.005
h_nerv*nerv	0.081	0.063	t*ent	-0.002	0.005
h_cardio	0.508††	0.028	t*image	0.004	0.003
h_car*cardio	0.337††	0.030			

†† p-value .01 or less; ‡ p-value .05 or less and † p-value .1 or less
Number of obs = 473466
LR chi2(75) = 60454.42
Prob > chi2 = 0.000
Pseudo R2 = 0.240
Log likelihood = -95648.548

Table 4. Effects on WTP of the Florida Merger Case

Bootstrap	Premerger WTP merged 1994 data	WTP separate 1994 data	predicted change, %	Postmerger WTP merged 1997 data	97-94 chg, %	prediction error, %
1	32011	25841	23.87	31041	20.12	3.03
2	32644	26253	24.34	30882	17.63	5.40
3	33191	26669	24.45	31466	17.99	5.20
4	32386	26147	23.86	30798	17.79	4.90
5	32382	26065	24.24	31222	19.79	3.58
6	32551	26172	24.37	31419	20.04	3.48
7	32334	26062	24.06	31076	19.24	3.89
8	32959	26488	24.43	30758	16.12	6.68
9	32492	26208	23.98	31090	18.63	4.31
10	32603	26203	24.43	31566	20.47	3.18
-	-	-	-	-	-	-
100	32365	26109	23.96	31382	20.20	3.04
Mean, all 100	32499	26205	24.02	31230	19.18	3.90
St. Dev	238.28	158.71	0.22	241.54	1.16	1.01

Table 5. Effects on WTP of the Florida Merger for Private Pay Patients

	Premerger WTP merged 1994 data	WTP separate 1994 data	predicted change, %	Postmerger WTP merged 1997 data	97-94 chg, %	prediction error, %
1	13283.02	11001.12	20.74	12628.21	14.79	4.93
2	13327.25	10998.04	21.18	12545.36	14.07	5.87
3	13671.18	11272.80	21.28	12852.51	14.01	5.99
4	13247.10	10971.62	20.74	12488.97	13.83	5.72
5	13394.20	11059.30	21.11	12653.26	14.41	5.53
6	13413.30	11060.78	21.27	12735.11	15.14	5.06
7	13318.08	10999.82	21.08	12642.60	14.93	5.07
8	13533.40	11161.35	21.25	12368.54	10.82	8.61
9	13294.61	11000.62	20.85	12646.59	14.96	4.87
10	13386.15	11052.42	21.12	12790.98	15.73	4.45
-	-	-	-	-	-	-
100	13418.01	11098.66	20.90	12751.50	14.89	4.97
Mean, all 100	13402.64	11086.55	20.89	12721.49	14.75	5.08
St. Dev	115.74	88.39	0.19	131.48	1.44	1.24

Table 6. Merger Effects on WTP of the Long Island Merger Case

	Premerger WTP merged 1996 data	WTP separate 1996 data	predicted change, %	Postmerger WTP merged 1999 data	99-96 chg, %	prediction error, %
1	75050.79	60133.69	24.81	76586.61	27.36	2.05
2	75472.76	60280.07	25.20	76747.95	27.32	1.69
3	75269.97	60027.30	25.39	76955.08	28.20	2.24
4	75664.98	60491.53	25.08	76952.70	27.21	1.70
5	75686.00	60246.48	25.63	77033.69	27.86	1.78
6	75764.84	60364.78	25.51	77372.72	28.18	2.12
7	75548.58	60329.90	25.23	77557.18	28.56	2.66
8	75948.16	60527.92	25.48	76709.77	26.73	1.00
9	74860.22	59921.97	24.93	77206.97	28.85	3.13
10	75972.28	60569.13	25.43	76761.76	26.73	1.04
-	-	-	-	-	-	-
100	75317.68	60052.65	25.42	77540.23	29.12	2.95
Mean, all 100	75551.76	60310.06	25.27	77065.36	27.78	2.01
St. Dev	358.42	234.84	0.18	294.32	0.71	0.63

Table 7. Effects on WTP of the NY Merger Case for Private Pay Patients

	Premerger WTP merged 1996 data	WTP separate 1996 data	predicted change, %	Postmerger WTP merged 1999 data	99-96 chg, %	prediction error, %
1	47328.78	38689.03	22.33	48930.28	26.47	3.38
2	47943.74	39028.07	22.84	49150.54	25.94	2.52
3	47515.60	38643.10	22.96	49219.37	27.37	3.59
4	47726.89	38877.08	22.76	49001.56	26.04	2.67
5	47828.55	38827.00	23.18	49134.83	26.55	2.73
6	48034.18	39004.84	23.15	49193.34	26.12	2.41
7	47971.07	38996.81	23.01	49349.01	26.55	2.87
8	48150.09	39119.80	23.08	48780.01	24.69	1.31
9	47473.61	38661.98	22.79	49125.09	27.06	3.48
10	47860.11	38888.04	23.07	49066.25	26.17	2.52
-	-	-	-	-	-	-
100	47690.09	38754.24	23.06	49245.11	27.07	3.26
Mean, all 100	47857.68	38916.35	22.98	49146.47	26.29	2.70
St. Dev	253.44	169.26	0.19	250.52	0.88	0.77

Table 8. Elasticity of Price with respect to WTP

Most Widely Treated[a]				Largest Discharge Frequency[b]			
DRG	α_d	Std. Err.	weight	DRG	α_d	Std. Err.	weight
14	1.290	0.137	0.036	14	1.290	0.137	0.042
15	0.391	0.278	0.015	15	0.391	0.278	0.018
24	0.317	0.333	0.012	88	0.877	0.163	0.039
25	1.015	0.401	0.013	89	0.070	0.238	0.036
79	1.096	0.231	0.013	97	0.512	0.340	0.021
82	0.839	0.287	0.012	121	0.758	0.174	0.026
88	0.877	0.163	0.034	122	0.671	0.218	0.028
89	0.070	0.238	0.031	127	0.909	0.103	0.055
96	1.383	0.380	0.014	138	0.856	0.168	0.026
97	0.512	0.340	0.018	139	0.375	0.316	0.019
121	0.758	0.174	0.023	140	0.849	0.104	0.055
122	0.671	0.218	0.025	143	-0.326	0.132	0.081
127	0.909	0.103	0.048	148	0.633	0.192	0.034
138	0.856	0.168	0.023	167	0.199	0.196	0.023
139	0.375	0.316	0.017	174	1.034	0.139	0.035
140	0.849	0.104	0.048	182	0.498	0.164	0.053
142	0.556	0.313	0.009	183	0.752	0.152	0.048
143	-0.326	0.132	0.071	204	0.490	0.278	0.021
148	0.633	0.192	0.030	209	0.995	0.175	0.036
167	0.199	0.196	0.021	214	0.392	0.260	0.023
174	1.034	0.139	0.030	215	1.095	0.099	0.053
180	1.220	0.299	0.010	243	1.026	0.242	0.025
182	0.498	0.164	0.046	294	1.060	0.279	0.021
183	0.752	0.152	0.042	296	1.432	0.203	0.022
197	1.143	0.171	0.012	320	0.979	0.222	0.017
198	1.169	0.212	0.012	358	0.253	0.141	0.064
204	0.490	0.278	0.019	410	1.289	0.162	0.044
243	1.026	0.242	0.022	416	1.297	0.267	0.022
277	1.033	0.228	0.010	494	0.274	0.319	0.016
278	0.310	0.365	0.010				
294	1.060	0.279	0.018				
296	1.432	0.203	0.019				
320	0.979	0.222	0.015				
321	0.708	0.338	0.008				
323	0.686	0.293	0.012				
324	0.522	0.304	0.014				
358	0.253	0.141	0.056				
359	0.198	0.097	0.102				
416	1.297	0.267	0.019				
449	1.153	0.285	0.010				
Overall Elasticity $\tilde{\alpha}$	0.627	0.032			0.683	0.011	
Predicted % increase in price due to merger	13.10%				14.26%		
Actual post-merger price increase	23.13%				24.68%		

Note: [a] The first category, "Most Widely Treated" DRGs is a selection of top 40 DRGs that are treated by the largest number of hospitals in Florida. It includes the 10 DRGs selected in Lynk (1995) and Keeler et al. (1999).

[b] The second category, "Largest Discharge Frequency" DRGs are those with the largest discharge frequency in the state for 1993-1994.

[c] If the 10 DRGs in Lynk (1995) and Keeler et al. (1999) are used, the overall elasticity is 0.862 and 0.837 for the first and second category respectively.

Table 9. Replacement Hospitals for Alternative Network Configuration

Merged Hospitals	Replacement Hospitals	Driving Time (minutes)	Distance (miles)
Columbia Hospital	Palm Beach Gardens	11	7.90
Palm Beach Regional	Bethesda Memorial	13	8.51
Palm West Hospital	Saint Mary's Hospital	37	23.65
JFK Medical Center	Bethesda Memorial	9	4.77
Average		17.5	11.21

Table 10. Effect of Mergers with Alternative Hospital Networks

Hospital Name	WTP with No Replacement	WTP With Single Replacement	Replacement Hospital
Columbia Hospital	1712.87	1518.76	Palm Beach Gardens
Palm Beach Regional	2598.4	2131.36	Bethesda Memorial
Palms West	2154.03	1968.41	Saint Mary's Hospital
JFK Medical Center	4611.37	4074.55	Bethesda Memorial
total	11076.67	9693.08	
WTP After Merger % Increase	13389.89 20.88%	13053.35 34.67%	Palm Beach Gardens
		13254.68 36.74%	Saint Mary's Hospital
		11831.86 22.07%	Bethesda Memorial
		With Multiple Replacements	Replacement Hospital
WTP After Merger % Increase		12920.87 33.30%	Palm Beach Gardens Saint Mary's Hospital
		11501.31 18.65%	Palm Beach Gardens Bethesda Memorial
		11700.4 20.71%	Saint Mary's Hospital Bethesda Memorial
		11372.51 17.33%	Palm Beach Gardens Bethesda Memorial Saint Mary's Hospital

References

Bellandi, Deanna, "TESTIMONY ENDS IN N.Y. ANTITRUST CASE," *Modern Healthcare*, September 1997, p. 17.

Binmore, Ken, Ariel Rubinstein, and Asher Wolinsky, "The Nash Bargaining Solution in Economic Modelling," *RAND Journal of Economics*, Summer 1986, *17* (2), 176–188.

Capps, Cory, David Dranove, and Mark Satterthwaite, "Competition and Market Power in Option Demand Markets," *RAND Journal of Economics*, September 2003, *34* (4), 737–763.

———, ———, Shane Greenstein, and Mark Satterthwaite, "The Silent Majority Fallacy of the Elzinga-Hogarty Criteria: A Critique and New Approach to Analyzing Hospital Mergers," *NBER Working Papers 8216*, 2001.

———, ———, ———, and ———, "Antitrust Policy and Hospital Mergers: Recommendations for a New Approach," *Institute For Policy Research Working Paper*, Feburary 2002.

———, ———, ———, and ———, "Geographic Market Definition in Hospital Merger Cases," Technical Report, Federal Trade Commission and Department of Justice Hearings on Health Care and Competition Law and Policy April 2003.

Ciliberto, Federico and David Dranove, "The effect of physician-hospital affiliations on hospital prices in California," *Journal of Health Economics*, January 2006, *25* (1), 29–38.

Cogswell, Susan, "A Comparison of Managed CareOrganizations in Connecticut," *State of Connecticut Insurance Department,*, 2002.

Cuellar, Alison Evans and Paul J. Gertler, "Strategic integration of hospitals and physicians," *Journal of Health Economics*, January 2006, *25* (1), 1–28.

Dranove, David and Richard Ludwick, "Competition and pricing by nonprofit hospitals: a reassessment of Lynk's analysis," *Journal of Health Economics*, January 1999, *18* (1), 87–98.

Ellison, Sara Fisher and Christopher M. Snyder, "Countervailing Power in Wholesale Pharmaceuticals," *MIT Dept. of Economics Working Paper*, July 2001, (No. 01-27). Available at SSRN: http://ssrn.com/abstract=277290.

Elzinga, Kenneth and Thomas Hogarty, "The Demand for Beer," *The Review of Economics and Statistics*, 1972, *54* (2), 195–98.

——— and ———, "The Problem of Geographic Market Delineation in Antimerger Suits," *Antitrust Bulletin*, March 1974, pp. 45–81.

Gal-Or, Esther, "Mergers and Exclusionary Practices in Health Care Markets," *Journal of Economics & Management Strategy*, 09 1999, *8* (3), 315–350.

Gaynor, Martin and William B Vogt, "Competition among Hospitals," *RAND Journal of Economics*, 2003, *34* (4), 764–785.

Green, Donald, Karen Jacowitz, Daniel Kahneman, and Daniel McFadden, "Referendum Contingent Valuation, Anchoring, and Willingness to Pay for Public Goods," Working Papers 010, University of California at Berkeley, Econometrics Laboratory Software Archive November 1995.

Guerin-Calvert, Margaret E., Robert F. Leibenluft, and Tracy E. Weir, "The FTC's Roud One Victory in its Challenge to the Evanston Northwestern Hospital Merger: What did the ALJ find, and What are the Implications?," *Hospitals and Heatlh Systems Practice Group Member Group Briefing*, 2005.

Haab, Timothy C. and Kenneth E. McConnell, *Valuing Environmental and Natural Resources: The Econometrics of Non-Market Valuation*, Cheltenham UK: Edward Elgar Publishers, 2003.

Jaspen, Bruce., "An Off Year for Consolidation," *Modern Healthcare*, 1998, *28*, 40–48.

Keeler, Emmett B., Glenn Melnick, and Jack Zwanziger, "The changing effects of competition on non-profit and for-profit hospital pricing behavior," *Journal of Health Economics*, January 1999, *18* (1), 69–86.

Kessler, Daniel and Mark McClellan, "Designing Hospital Antitrust Policy to Promote Social Welfare," *NBER Working Papers 6897*, 1999.

Lutz, Sandy, "Columbia/HCA-Healthtrust merger faces closer look from feds, state enforcers," *Modern Healthcare*, November 1994.

——— **and Karen Pallarito**, "Columbia Keeps on Growing," *Modern Healthcare*, March 1995.

Lynk, William J., "The creation of economic efficiencies in hospital mergers," *Journal of Health Economics*, December 1995, *14* (5), 507–530.

McFadden, Daniel, "Contingent Valuation and Social Choice," *AMERICAN JOURNAL OF AGRICULTURAL ECONOMICS*, November 1994, *76* (4), 689–708.

———, "Computing Willingness-to-Pay in random utility models," in James C. Moore, Raymond Riezman, and James R. Melvin, eds., *Trade, Theory and Econometrics: Essays in Honor of John S. Chipman*, 29 West 35th Street, New York, NY 10001: Routledge, 1997, pp. 253–274.

———, "Measuring Willingness-to-Pay for Transportation Improvements," in T. Grling, T. Laitila, and K. Westin, eds., *THEORETICAL FOUNDATIONS OF TRAVEL CHOICE MODELING*, Amsterdam: Elsevier Science:, 1998, pp. 339–364.

McQuiston, John T., "U.S. and Two Hospitals Battle Over Merger on Long Island," *The New York Times*, August 1997, p. Section B Page 5.

Melnick, Glenn and Emmett Keeler, "The effects of multi-hospital systems on hospital prices," *Journal of Health Economics*, March 2007, *26* (2), 400–413.

Pallarito, Karen, "TESTING ANTITRUST BOUNDARIES: N.Y. HOSPITAL MERGER PROBE MAY BREAK NEW GROUND," *Modern Healthcare*, March 1997, p. 12.

Sacher, Seth and Louis Silvia, "Antitrust Issues in Defining the Product Market for Hospital Services," *International Journal of the Economics of Business*, July 1998, *5* (2), 181–202.

Town, Robert and Gregory Vistnes, "Hospital competition in HMO networks," *Journal of Health Economics*, 2001, *20* (5), 733–753.