Can Empirical Demand Models Assist in CON Comparative Reviews?

A Case Study in Florida

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Abstract

Certificate-of-Need (CON) programs for new hospital construction are intended to foster the best selection among competing hospital applications, given demands for hospital care in the community. Yet, the merits of CON depend in part on the quality of its comparative review process. This paper examines a case study in Florida to illustrate the utility of empirical evaluations using patient choice models. We estimate such models to show how patients would respond to a change in hospital choices. By simulating the welfare effects of the proposed hospitals, we can further predict how prices of hospital care differ by applicant. Results suggest that empirical analysis using data on patient choice of hospitals may better inform the review process. At the same time, however, it may not give a unique ranking without additional analysis of the fixed costs of proposed services in the context of existing market-wide capacity.

1. Introduction

Proposals to build and operate new acute care hospitals are often subject to strict state regulations, known as Certificate of Need (CON) laws, that entail extensive review to ensure planning objectives are met. The process is intended to foster the best selection among competing hospital applications, given demands for hospital care in the community. Yet, the merits of CON hinge on the success of its comparative review process. Despite its intended purpose of restraining health care costs in hospitals, CON laws are often seen as a failure, according to many researchers, policy makers and experts in the field. Problems include investment distortions (Salkever and Bice 1976), allocative inefficiency (Feldstein 1988; Eakin 1991; Havighurst 2005), monopoly profits associated with indigent care subsidies (Campbell and Fournier 1993), and adverse effects on costs and quality of care (Ford and Kaserman 1993).

CON can be seen as an allocation mechanism where firms submit proposals for facilities and services that they will provide in the future and show that they have credentials to carry out the project as specified. Competing proposals are judged and compared by a government agency and the rights to provide new services are then granted to the one that meets the criteria or preferences best. The goal may be to foster an efficient market where the public needs are met and the resulting competition among firms leads to lower prices. CON entails uncertainty to applicants, who know what the criteria are but do not know how important each criterion is. Each applicant may be to some extent uncertain about how each criterion is weighted.

A key consequence of this allocation process is that scoring on each element of a proposed hospital service configuration is subjective, reflecting the views of the relevant authority. A certificate of need may be awarded to the wrong party if the additional demand (or benefits) for e.g., a new obstetric program, as perceived by the agency exceeds what would otherwise be determined by market conditions and patients' preferences in the community. Furthermore, because of its subjective nature, the evaluation process can be manipulated by interest groups. It was suggested early on that hospital executives with more political skills were more likely to obtain the CON license.[1] Of course, an optimal decision might still be reached if one applicant dominates others by performing at least as well as the others on all criteria and strictly better than them on at least one criterion. In principle, one option might dominate all others, but in practice it is unlikely and the judgment of regulatory authority will often determine the outcome.

It is not well-established how often the best applicant is selected in practice. Moreover, in the normal process of review no empirical evidence is generated about the costs or consequences of awarding the CON to the wrong applicant. While economic evidence has in the past been employed in limited ways, the legal process has most heavily relied on health planning methods. These methods are largely descriptive and may overlook how local patient respond to variations in choices of hospital care, parameters that are possible to assess with modern empirical methodologies. A more inclusive method is needed to estimate how much a proposed hospital will benefit the community. One method is to infer the willingness-to-pay for each alternative as revealed empirically by how patients and doctors compare these values across available options. The revealed preference method deals explicitly with uncertainty and multi-criteria assessment, common challenges in comparing different hospital proposals. This approach has become popular in health economics with the help of widespread digital recording of patients' discharge information.

In this paper we explore a specific case study in Florida of the comparative review process to evaluate proposals for new hospital construction. We argue here that empirical demand models of patient choice of hospitals can be useful in understanding the relative merits of competing proposals. Available patient discharge data provide timely records of hospital care needed for conducting empirical analysis prospectively, before CON actions are final. Details such as the range of hospital services, locations and many other characteristics of the new hospital are all included in the proposed CON application. Our approach uses conditional logit models of patient choice to estimate the *additional* contribution of a hospital to patients' utility or Willingness-to-Pay (WTP); in other words, it measures the *net* benefit of a proposed hospital to the community. These benefits are derived from the match between the services proposed by the applicant, its location, and preferences of patients in the service area. In addition, prices for hospital care can be affected when applicants currently own hospitals in the local market because the selection among applicants has implications for the post-entry market structure. We simulate both the welfare effects and price impacts that would likely occur based on the selection among CON applicants. We are able to account for multiple criteria because this methodology incorporates how all attributes of the project taken jointly affect consumers' utility. Finally, the model helps to control for the uncertainty problem by aggregating patients' utility across all possible medical diagnoses weighted by the conditional probability of each.

The paper is organized as follows: we discuss first, in the context of some recent literature, how the marginal value of a new hospital is determined, using the conditional logit model, and then link the changes in WTP due to a new hospital entry on the level of prices for hospital care. After discussing CON law in Florida and the details of our case study, the next sections provide our empirical analysis of competing CON applications in Clay County, Florida during the period 2005-2007 to illustrate the utility of empirical evaluations using patient choice models. Results predict how patients would respond to a change in hospital choices and how selecting the winning applicant would affect the performance in the local market based on the expected benefits to the community and their predicted effects on the prices of hospital services. A discussion of issues and our conclusions follow.

2. Measuring the Value of a New Hospital

With detailed patient and hospital information, researchers can now estimate how important each hospital is to the local residents in terms of the incremental utility it brings to the community. Examples of this methodology are Town and Vistnes (2001), Capps et al. (2003), and, more recently, Gowrisankaran, Nevo and Town (2013). These studies estimate the additional contribution of each hospital to the total utility of the community based on the actual choice behavior. One finding from these studies quantifies the increased value to the community of adding a new hospital in terms of giving patients more options, although this effect diminishes when the number of existing hospitals is large. The incremental value takes into account non-price characteristics of choice options each patient faces, including travel time, nature of illness, convenience and the patient-facility match.

In addition to enhancing options for hospital care, a second distinct welfare effect is likely to occur in negotiated prices. The price of hospital services, negotiated with health plan carriers and then reflected in insurance premia, will normally fall and converge to competitive levels as new hospitals are added to the market. In theory, a new independent hospital competitor will weaken the market power of the existing providers. Recent literature shows that willingness-to-pay captures a key leverage factor in the negotiation between health plans, such as Managed Care Organizations (MCOs), and hospitals.

Assessing the overall value or community benefit of a hospital in a local market, including the effects of a new entry on the local prices of hospital care, must recognize the unique role of intermediation by payers on behalf of patients. Capps et al. (2003) consider the hospital market as an ‘option demand’ market in which managed care organizations (MCOs) negotiate with hospitals for contracts to provide care on behalf of customer/members.[2] Contracts determine which local hospitals are included in the network and the payment obligations of the plan. Consumers (or employers as their representative) then decide which network to join.

While consumers’ hospital choices may be restricted by the network, prices play little or no part in the choices made at the time when a patient experiences a medical care episode requiring hospital care. Members of managed care plans, after paying the premium, face little or 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 services in this market does not remove potential concerns about market power resulting from co-located hospitals owned by the same company. In antitrust law, hospital merger analysis remains focused on the effects on prices (Moriya et al. 2010). Similar concerns may be present in the CON comparative process. The usefulness of WTP measures requires some understanding of how hospital ‘prices’ relate to patients’ WTP and how new entry may affect prices in this model.

Hospital valuation and willingness-to-pay

Assume that a local market has a set of hospitals present and a new one to be constructed after the CON approval. 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.[3] The MCO negotiates individually with the existing 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. We first define the WTP measurement in a logistic model. After WTP is defined, we discuss some literature on negotiations between MCOs and hospitals and linking hospital prices to the WTP measurement.

The indirect utility individual i gets from going to hospital j is:

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

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. When an existing managed care plan includes hospital j as well as k in the network, a patient will choose hospital j over k if:

$$U_{ij} - U_{ik} > 0 \Rightarrow a_{ij} - a_{ik} > \varepsilon_{ik} - \varepsilon_{ij} \tag{2}$$

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 network G, follows a familiar logistic distribution:

$$s_{ij}(G, a_{ij}) = \frac{\exp(a_{ij})}{\sum_{k \in G} \exp(a_{ik})} \tag{3}$$

In this model, the MCO with a total of N enrollees' yields maximum expected utility given p and network G [4]:

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

For example, with two hospitals already in the network, the MCO can negotiate to include the third hospital (a newly constructed one after CON approval) in its network if additional costs are less than its additional benefit to the enrollees:

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

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

$$N * (p - p') < \sum_{i=1}^{N} [\ln(\exp(a_{i1}) + \exp(a_{i2}) + \exp(a_{i3})) - \ln(\exp(a_{i1}) + \exp(a_{i2}))] \tag{5}$$

The term on the right side of the inequality condition is the willingness-to-pay (WTP) for the new hospital, measuring the *incremental* contribution of hospital 3 in network G to the aggregate patients' utility. Specifically, it measures the change in the maximum utility[5], summed over all patients, when hospital 3 is added to the network, given that the remaining hospitals in G are already present.

In general, we denote $WTP_j^i(G, a_{ij})$ for the WTP of hospital j to patient i and $WTP_j(G)$ for the WTP of hospital j for all N enrollees in managed care network G. Combining equation 5 with 3 gives the individual and the aggregate WTP values:

$$WTP_j^i(G, a_{ij}) = \ln(\sum_{G} \exp(a_{ij})) - \ln(\sum_{G'} \exp(a_{ij})) = \ln\left[\frac{1}{1 - s_{ij}(G, a_{ij})}\right]$$

$$WTP_j(G) = \sum_{i=1}^{N}(\ln(\sum_{G}\exp(a_{ij}))) - \sum_{i=1}^{N}(\ln(\sum_{G'}\exp(a_{ij}))) = \sum_{i=1}^{N}\ln\left[\frac{1}{1-s_{ij}(G,a_{ij})}\right] \qquad (6)$$

Where $G = G' + j$

Similarly, $WTP_{jk}(G)$, the joint WTP of hospital j and k in managed care network G, i.e. the additional utility hospitals j and k together bring to the network:

$$WTP_{jk}(G) = \sum_{i=1}^{N}(\ln(\sum_{G}\exp(a_{ij}))) - \sum_{i=1}^{N}(\ln(\sum_{G'}\exp(a_{ij})))$$

$$= \sum_{i=1}^{N}\ln\left[\frac{1}{1-s_{ij}(G,a_{ij})-s_{ik}(G,a_{ik})}\right] \qquad (7)$$

Where $G = G' + j + k$

The empirical analysis in this study uses the conditional logit model to estimate the underlying parameters and predict s_{ij} across all medical diagnoses.

The previous discussion assumes that p, the rates paid to hospitals, are set exogenously. To model how those rates are determined under the managed care contract, Capps et al. (2003) imagine a bilateral negotiation between the MCO and each of many *independent* hospitals and consider the Nash bargaining solution. 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 will be split between parties based on the bargaining weights of the MCO relative to the hospital and vice versa. 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 (2010) and Gal-Or (1999) also use the Nash Bargaining Solution to model the negotiation between suppliers and buyers.

In one recent paper, Dranove et al. (2011) examines the effect of the WTP leverage in a structural model of bargaining with a single payer (health plan) and many hospitals. The model explores boundedness on the amount of foresight parties have regarding their alternative choices and the effect of one hospital being excluded from the remaining ones. The overall costs of health plans mirror the changes in the bargaining strength or weakness of the hospitals. When local hospitals engage in mergers, for example, their joint bargaining position is strengthened and these changes may lead to an increase in the negotiated prices for hospital care.

To sum up this section, the conditional logit model, along with other generalized multinomial models, provides an empirical basis for estimating the incremental value of a new hospital for regulatory purposes in CON proceedings. Generally the addition of a new hospital adds some positive incremental value, although at a diminishing rate when the number of existing hospitals is large. The price of hospital services, as reflected in insurance premia, will normally fall as new hospitals are added to the market.

While, in theory, a new independent competitor will weaken the market power of the existing providers, there is an exception to the pro-competitive effect that has important implications. When a new hospital CON is awarded to an applicant currently present in the market, the relevant WTP for the two combined is higher than the sum of the same two as independent entities, $WTP_{12}(G) > (WTP_1(G) + WTP_2(G))$. Thus, CON decisions that induce large changes in WTP for co-owned hospitals may result in a corresponding increase in the rates paid to hospitals for patient care that should raise valid concerns about harm to consumers. The value of the WTP measure is that it imputes effects that can vary considerably by the geographic location of the managed care members. These effects may be overlooked when confining attention to fixed sets of competitors in the market.

3. CON Law and a New Hospital for Clay County, Florida

Since the 1987 Congressional repeal of mandated CON, fourteen states have dropped these programs altogether. Today, of the thirty-six states and the District of Columbia that practice CON laws, twenty-five use a comparative review process to select project proposals, requiring evaluations of competing applications in the same local market for the CON.

The coverage and review threshold vary considerably across these states. According to the American Health Planning Association (AHPA 2006), Alaska covers 28 types of health care services and equipment, the highest coverage rate of all states, while Louisiana has the lowest coverage, including only Intermediate Care Facilities for the Mentally Retarded (ICF/MR) and Long Term Care/Nursing Homes. The dollar threshold also varies across states. In Florida, for example, a hospital expenditure of any amount would require CON approval. In Massachusetts, a CON license is required only if the hospital expenditure exceeds $12.5 million. The CON filing/review fees and costs of litigation also vary significant across states.

States are also very different in enforcing the CON laws. AHPA (2006), in a 2005 survey of the 23 states that regulate acute care hospital beds, found that 19 approved over 90% of applications. A dozen states and D.C. approved *every* hospital project in 2005. The most discriminating state was Alabama, which approved only 9.86% of total proposed dollar amount (approved $41,523,738 out of $285,004,825). It was followed by South Carolina (39.21%), Florida (51.94%), and Tennessee (77.07%).

In our case study from Florida, the state's Agency for Health Care Administration is responsible for the implementation of CON, following statutory guidelines and judicial precedence for review criteria.[6] These criteria include improved accessibility of the majority of residents to hospital care, meeting the current and future healthcare needs of the community, applicant's financial health and its record of charity care, prevention of adverse financial impact on existing facilities, and promotion of competition, among other things.

Florida historically has had low approval rates and high appeal rates. From 1980 to 2000, the lowest approval rate for hospital projects was 33.33% in 2000. 1994 saw the highest appeal rate of 72.52%. This suggests that Florida is strict in enforcing the CON laws and their decisions tend to be unpopular if not controversial.

In 2005, three hospital operators in North Florida each applied for a license to construct a new hospital in Clay County, Florida: the non-profit Baptist Medical Center ("Baptist," or alternately "BMC Clay"), a second non-profit St. Vincent Medical Center ("St. Vincent," or "SVMC Clay") and the for-profit Orange Park Medical Center ("Orange Park," or "OPMC Clay"). Orange Park was the only incumbent hospital located in the county at the time, although local residents could to some degree choose more distant hospitals. A location map is shown in figure 2 and proposed hospital services are listed in table 1.

Both the initial evaluation of the applications and subsequent legal proceedings that followed the agency's ruling reflected in part a health planning approach. Health planners present rich contextual details and large volumes of descriptive data about demographics, hospital care patterns in the local areas, market shares and revenue projections, traffic flows and travel times. These efforts provide important ingredients to the evaluation but do not present a unified assessment of aggregate benefits and comparative merit. We argue that estimation of willingness-to-pay models can provide useful guidance for comparing proposals by incorporating data on revealed preferences and choices from the local community. The advances that have eased implementing multinomial choice modeling, combined with improved electronic data systems on patients in hospitals, make it feasible to obtain a clearer picture of the relative benefits among the alternatives, in many if not all dimensions of interest to public welfare.

4. Analysis of the Pricing of Hospital Services

We begin with an analysis of the pricing history of the seven local hospitals by constructing composite price indexes and examine whether the levels of prices significantly vary among the existing hospitals owned by the applicants in the situation prior to the entry of a new hospital. Locations and the selection of hospitals and patients are discussed in detail in the appendix.

Keeler et al. (1999) and Melnick and Keeler (2007) use similar methods to construct hospital-specific price indexes or "standardized prices" for each year from 1986 to 1994 in California and from 1999 to 2003, respectively in the two studies. The authors first compute the net revenue for patients in each hospital within each of the 10 common diagnostic categories called "Diagnostic Related Groups" (DRGs) by multiplying each patient's listed charges by the hospital's average discount factor for private-pay patients at the hospital.[7] The discount factor is calculated as the ratio of net revenue to gross charges from the hospital financial data for private-pay patients.[8]

The logarithm of the net revenue per patient day within each diagnostic category in each year is regressed on hospital dummy variables, patient age, gender, race, whether case routine, mortality of the patient, and length of stay. By regressing prices separately by diagnostic categories, we control for potential differences in prices due to different hospitals offering diverse mixes of services. In addition, the regression controls for patient differences within DRGs across hospitals. Such adjustments are obviously important, since even within the same diagnostic categories, patients who are in more severe conditions would require intensive care and lead to higher charges. The 10 selected diagnostic categories represent common diseases that can be treated without highly specialized equipment; thus they are performed by the greatest percentage of all hospitals. The 10 fixed effects (the hospital-DRG dummy coefficients) for each hospital are combined into a standardized price index weighted by the average proportion of patients in that diagnostic category in the entire sample. We can infer price differences across hospitals from these standardized price indexes, and are able to create price indexes for these sets of diagnostic categories.

From inpatient discharge data of 2002 to 2005, we select only those patients with commercial insurance, including managed care and preferred provider plans. Charges for private pay patients are negotiated in bargaining between hospitals and payers, and hence are more likely to be affected by conditions affecting hospital competition. In contrast, Medicare and Medicaid prices are set exogenously by federal reimbursement policy and are unlikely to be influenced by hospital market power.

It is infeasible to incorporate every diagnostic category in the index construction, especially since the proposed hospitals plan to treat a limited range of patients; consequently four alternative sets of price indexes are constructed. The first two indexes are based on regressions including only the top-50 and top-10 "most widely treated" diagnostic categories in the state.[9] Alternatively, we select DRGs for inclusion in the index from top-50 and top-10 diagnostic categories with the "largest discharge frequency" statewide.[10]

An additional set of regression-based indexes differ in terms of whether patient discharge frequencies are compiled from the data on local patients alone or from patients across the whole state. The first group includes diagnostic categories based on patients in District 4, a collection of Florida counties including Baker, Clay, Duval, Nassau and St. Johns counties, which make up the main service areas for the 7 hospitals. We selected top-50 and top-10 "most widely treated" DRGs in this local market; top-50 and top-10 DRGs with the "largest discharge frequency".[11] A final category of indexes we report matches the 10 DRGs used in Keeler et al. (1999), Melnick and Keeler (2007) and Lynk (1995).

For each diagnostic category, we regress the log of net price per day:

$$\ln(netp / los)_{ijd} = x'_{ijd}\, b + \alpha_{jd} + \varepsilon_{ijd} \qquad (8)$$

where observations are on patient i in diagnostic category d at hospital j. The dependent variable, $netp / los$, is an estimate of the net price per day.[12] The explanatory variables x_{ijd} control for length of stay (los), patient demographics (gender, race and age), discharge status, source and the year of admission, and α_{jd} is the fixed effect for hospital j in DRG d. A weighted average of the fixed effects, α_{jd}, will be used to obtain the price index for hospital j: $P_j = \sum_d wt_d \alpha_{jd}$, where wt_d are weights by patient volume.

Table 3 reports the log price regressions based on the nine sets of DRGs. In each regression, Orange Park is the omitted hospital and the hospital specific effects are relative to it. Recall that Orange Park was awarded the CON in the initial ruling by the agency. The weighted fixed effects for each hospital thus give us the price differences, relative to Orange Park after controlling for patient attributes. The first four columns are based on diagnostic categories of statewide patient discharges whereas columns 5 to 8 are based on diagnostic categories of patient discharges in the local market. The last column is the result using the 10 DRGs in Keeler et al. (1999), Melnick and Keeler (2007) and Lynk (1995). Compared to Orange Park, both St. Vincent and Baptist charge significantly less for the same services across all the selected diagnostic categories, although it is inconclusive which of these two hospitals charges the lowest price. For instance, for the top-50 DRGs with the “largest discharge frequency” statewide, St. Vincent and Baptist charge 24% and 22% less than Orange Park respectively. The largest difference is for the statewide top-50 “most widely treated” DRGs (36% and 32% for St. Vincent and Baptist respectively); while the smallest difference is found in the top-10 DRGs with the “highest discharge frequency” in the local market (15% and 13% for St. Vincent and Baptist respectively). In each case, the difference is significant at 1% confidence level.

In 7 out of the 9 diagnostic categories, the prices in St. Vincent are lower than Baptist, though the differences are not statistically significant. For instance, in the first column, St. Vincent charges 4.7% lower than Baptist with a standard error of 9.12%. Our finding is consistent with the parties’ claim that St. Vincent and Baptist charge lower prices than Orange Park because, unlike the situation facing Orange Park as the sole hospital in the county, the other two operate closer to the urban center of Jacksonville where the market is relatively competitive with 6 nearby hospitals[13] in the local community competing for the MCO contract.

Baptist Medical Center-Beaches and Memorial Hospital Jacksonville also have lower price levels than Orange Park. The former charges 12% to 26% less than Orange Park and the latter 11% to 23% less depending on the diagnostic category. The price level at St. Luke’s Hospital is 21% to 30% higher than the benchmark Orange Park. The main reason may be that St. Luke’s is affiliated with the Mayo Clinic and treats patients with severe conditions. The pricing patterns for Shands Jacksonville Medical Center vary depending on DRG categories. For 6 out of the 9 sets of diagnostic categories, including top-50 and top-10 DRGs with "highest discharge frequency" statewide; and the four DRG categories based on local market, Shands has a higher price level ranging from 3% to 17%. For top-50 and top-10 statewide "most widely treated" DRGs and the 10 DRGs based on Melnick and Keeler (2007), Shands charges 9% to 17% lower than Orange Park. We thus did not find a consistent pricing pattern for Shands Jacksonville Medical Center.

Previous research, including Abraham et al. (2007), Dranove et al. (1993), Staten et al. (1988), Dranove and Ludwick (1999) and Melnick et al. (1992), finds that competition among hospitals leads to lower prices. In the current study, we also find that being the only hospital in Clay County, Orange Park is able to charge at least 10% more compared to St. Vincent and Baptist in central Jacksonville, arguably a more competitive market than Clay County.

5. Welfare and Price Impacts of the New Hospital

Based on hospital capacity and occupancy rate data, the Florida Agency for Health Care Administration (AHCA) ruled that the construction of a new hospital is justified for providing medical care for the fast growing population in Clay County, Florida.[14] The question for CON regulators remains as to which one of the proposed hospitals provides the highest benefit to the community. Empirical demand models in general, and the WTP method in particular, provide a new approach to quantify these welfare effects. Patient preferences are revealed in their choice behavior and can be measured by the empirical model. The estimated parameters in the model can then be used to calculate the patients' expected maximum utility after a new hospital is introduced. We first estimate the empirical model including a vector of hospital characteristics for control types (for profit, not for profit, or government), teaching status, nursing intensity, capital intensity.

The model controls for services offered by hospital, the travel time from patient's home to the hospital, as well as detailed patient demographic and clinical information.[15]

The estimated parameters from the model are used to measure the indirect utility from the addition of a new hospital into the area. To estimate the value of aggregate utility, we need to determine the service area by the new hospital.[16] We use the joint 16 zip codes listed in table 4 as the service area of the new hospital, as these were the areas explicitly proposed in the CON applications. The last column is the primary service areas for Orange Park in the application, consistent with the choice sets constructed from 2005 hospital inpatient discharge data. The proposed service areas of the three hospitals overlap, while BMC Clay proposes to serve a larger area. BMC Clay and SVMC Clay also share some of the zip codes currently served by Orange Park. As a result we expect that a new hospital by either Baptist or St. Vincent would attract patients away from the existing provider, Orange Park, and thereby increase competition in the local market.

Bootstrap methods provide the estimated standard errors of the aggregate utility for patients in proposed service areas after introducing new hospitals. The first column in table 5 is the aggregate patient utility from existing providers. Column 2 and 3 are the utility from adding the new hospital, BMC Clay, and the percentage increase from current utility level. Column 4 and 5 are the level and percentage change in utility from OPMC Clay. The last two columns are results for introducing SVMC Clay. The average utility (standard error) after introducing BMC Clay, OPMC Clay or SVMC Clay is 34.20% (5.30%), 12.84% (3.36%), and 24.66% (2.46%) higher, respectively than the current level. The increase in utility is statistically significant for all three new hospitals, while the increase generated by BMC Clay and SVMC Clay is significantly larger than OPMC Clay. The utility increase between BMC Clay and SVMC Clay is not statistically different.

The results suggest that the new hospital proposed by either Baptist or St. Vincent will benefit the local community more than the one proposed by Orange Park. However, before we reach this conclusion, we need to examine the price effects of the new hospital. In theory, a new competitor will weaken the market power of the existing providers. In our case, BMC Clay and SVMC Clay will both increase competition in the market and lead to lower prices. On the other hand, OPMC Clay, a new hospital owned by the incumbent firm, will increase the bargaining power of the hospital and lead to higher prices.

To predict the magnitude of these price changes, we re-estimate equation 8 with the panel data from 2002 to 2005:

$$\ln(netp / los)_{ijd} = x'_{ijd}\, b + \alpha_d \ln(WTP_j) + \varepsilon_{ijd} \tag{9}$$

Variables are the same as in equation 8. Observations in the regression are commercial insurance (including health maintenance- and preferred provider- plan) patients discharged from the seven hospitals in district 4 from 2002 to 2005. Corresponding WTPs for each hospital in each year are estimated based on the formula in equation 6 and equation 7. Using patient frequency weights by diagnostic categories, wt_d, a weighted average of α_d, $\tilde{\alpha} = \sum wt_d \alpha_d$ gives the measure of the overall elasticity of prices with respect to WTP. Nine elasticities are calculated for each of the nine diagnostic categories defined in section 4. The highest elasticity (standard error) is 0.874 (0.101) for top-10 DRGs with “highest discharge frequency” statewide, while the lowest is 0.718 (0.169) for the top-50 “most widely treated” DRGs statewide. The elasticities are positive and significant in all nine cases.

To predict the price changes following the entry of the new hospital, we measure the price index for hospital j, $P_j = \sum_d wt_d \exp(\ln(netp/los)_{d_j})$, evaluated at the patient-DRG mean characteristics for hospital j in 2005. Note that all three applicants operate existing hospitals in the broad geographic area of District 4, although Orange Park is the only one nearby in Clay County itself. This co-ownership requires that we consider the enhanced bargaining position of the affiliated hospitals relative to the insurers when the new hospital enters. Alternately, in the case where we assume Baptist is granted the CON certificate, we estimate the joint WTP for Baptist and BMC Clay and the new WTPs for the other six hospitals.[17] These new WTPs together with the patient-DRG mean characteristics in 2005 are used to construct the new price index, $\overline{P}$ and to calculate price change in each hospital, $\frac{\overline{P_j}-P_j}{P_j}$. Denote w_j the frequency weight for hospital j based on patient volume for the seven local hospitals and wl_j the weight for hospital j based on patient distribution in the 16 zip codes (service areas of the new hospital),

$$\frac{\sum_j w_j * \overline{P_j} - \sum_j w_j * P_j}{\sum_j w_j * P_j} \tag{10}$$

gives the overall price impacts of the new hospital on all patients in District 4, while

$$\frac{\sum_j wl_j * \overline{P_j} - \sum_j wl_j * P_j}{\sum_j wl_j * P_j} \tag{11}$$

is the price change for patients in a smaller market, the service area of the new hospital. Both w_j and wl_j are predicted patient volume based on the conditional logit model.

Table 6 reports the results of the predicted price impacts under different scenarios for nine sets of diagnostic categories. In scenario 1 in table 6, when the CON is awarded to Baptist, for top-50 “most widely treated” DRGs locally, prices in Shands, St. Luke, St. Vincent and Orange

Park will decrease with the largest decrease (8.76%) induced upon Orange Park. This result is expected because the new hospital BMC Clay is a direct competitor for Orange Park in the same area. The increase of the joint bargaining power of BMC Clay and Baptist leads to a small price increases of about 1.2%.

Weighted by predicted patient volume in District 4, the new Baptist-affiliated hospital generates a very small price decrease of 0.72%. If we focus on patients in the service area of the new hospital (an area including 16 zip codes), price would decrease by 3.27%. In the second scenario, however, when OPMC Clay is allowed to build the new hospital, results are quite different. The model now predicts that there will still be a small decrease in price in the other 6 hospitals. Orange Park, on the other hand, is predicted to raise its price by 7.69% due to the increased market power brought by the new OPMC Clay. For a wide market including all patients in District 4, the overall price decreases about 0.7%. However, the harm to patients in proposed service areas is rather large with a price increase of 1.8%, which implies a price difference of about 5% between this scenario and scenario 1 or 3. This pattern is not sensitive to the alternative assumptions. For example, the final 3 columns show similar effects based on the original Keeler study's 10 DRG index components.[18]

Despite different weights and diagnostic categories, we find that if Orange Park were to be granted the CON, prices in Orange Park would increase 7% to 11%. The overall price increase for patients in proposed service areas would be about 2%. On the other hand, BMC Clay (or SVMC Clay) would lead to a price decrease of about 8% to 10% for existing Orange Park. Although the new hospital would increase the price in Baptist (or St. Vincent) by about 1%, there would be a 3% decrease for patients living in the 16 zip codes.

Overall Comparison of Applicants

Using parameters estimated from the conditional logit model, we measure the change in total utility for patients residing in the proposed service areas. We find unambiguous welfare gains when any of the proposed hospitals is permitted entry. There would be a significant increase in patients' utility by 34.20%, 12.84%, and 24.66% after introducing BMC Clay, OPMC Clay or SVMC Clay respectively. Thus, the model predicts that the increase generated by BMC Clay and SVMC Clay is significantly larger than OPMC Clay, but the differences between BMC Clay or SVMC Clay are not statistically different. Furthermore, if the new hospital is owned by either Baptist or St. Vincent, the existing provider, Orange Park, will be induced to lower its price by 7% to 11%, leading to an overall mean price decrease of about 3% for local residents. If the new hospital is OPMC Clay owned by the incumbent hospital, however, it will increase its bargaining power and increase the price at Orange Park by about 8%, or an overall mean price increase of 2% for local residents.

The results suggest that the new hospital proposed by either Baptist or St. Vincent will benefit the local community more than the one proposed by Orange Park. Of the three applicants, Orange Park is the only incumbent provider in Clay County. As a result, we find that Orange Park charges higher prices compared to the other two applicants who operate in a more competitive market in the nearby metropolitan area. Because both alternative proposals, BMC Clay and SVMC Clay, are predicted to generate community benefits and lower prices of similar magnitude, choosing between them must rest on other considerations.

It is interesting to note what transpired in this case. The agency initially decided in favor of awarding the CON to the incumbent Orange Park over the others, downplaying the incumbent monopoly potential. After a three-month hearing, however, an administrative hearing officer, Judge Stampelos reversed the ruling and awarded the CON to St. Vincent in December 2007. In June 2008, the agency gave the final approval to St. Vincent's Medical Center, ending three years of legal delays. The new hospital construction was further delayed, in part due to the recession, and is scheduled to open in October 2013.

6. **Conclusion**

The CON comparative review for hospital construction raises complicated issues of comparison among competing applications based on a broad set of criteria. Cases like the one studied here are likely to come up often and be hotly contested, given the substantial economic value of CON licenses. Some comparisons can be done relatively easily, while others such as the welfare and price impacts of the new hospital can be difficult to carry out. In this study, we adopt the willingness-to-pay method and use the 2005 CON application in Clay County, FL to compare the welfare and price impacts of the proposed hospitals.

Although we provide a single case study, the methodology can be applied in many similar instances of comparative reviews. We have shown that empirical analysis based on widely available patient discharge and hospital financial data can be useful in the CON comparative process. While there would be resistance to introducing sophisticated models into the judicial proceedings, in other areas such as antitrust law the adoption of empirical analysis incorporating structural modeling is becoming a more routine part of merger evaluations. The analysis here provides an estimate the marginal value of each proposed hospital to local residents, as well as the impacts on the price of hospital care to privately insured patients.

On December 3, 2007, Administrative Law Judge Charles Stampelos recommended the Agency enter a final order approving St. Vincent's Medical Center, Inc.'s CON application and denying the other two applicants.[19] On June 2, 2008, the Florida Agency for Health Care Administration gave the final approval to St. Vincent's Medical Center, ending a lengthy approval battle of almost three years. According to these orders, the decision reflected two concerns, among other things. First, allowing the new hospital to be owned by Orange Park Medical Center in lieu of the other alternatives would sacrifice an opportunity to introduce a new competitor into the area. Our empirical results confirm this effect by showing favorable price effects under the either of the alternatives SVMC Clay or BMC Clay relative to Orange Park.

The second issue cited by the administrative law judge was the need to provide adequate capacity for obstetrical services; the decision placed some weight on the applicant proposing to provide this service. This issue highlights something not easily resolved within our model. Since the WTP method does not directly address the efficiency effects of changes in market-level capacity, additional analysis would be needed to determine which proposal contains the efficient configuration of services, given the existing capacities in the local area. Since the range of services provided by the new hospital can be easily changed in the future, however, selecting CON applicants along these lines would seem to be misguided.

References

Abraham, Jean M., Martin S. Gaynor, and William B. Vogt. 2007. Entry and Competition in Local Hospital Markets. *The Journal of Industrial Economics* 50(2):265-288.

American Health Planning Association (APHA). 2006. *The 2006 National Directory: State Certificate of Need Programs, Health Planning Agencies*. Technical Report: National Bureau of Economic Research.

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

Campbell, Ellen, and Gary M. Fournier. 1993. Certificate-of-need deregulation and indigent hospital care. *Journal of Health Politics, Policy and Law* 18(4):905-927.

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

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

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

____________, Mark Satterthwaite, and Andrew Sfekas. 2011. Bargaining and Leverage in Option Demand Markets. Working Paper, Northwestern University Kellogg School of Management.

____________, Mark Shanley, and William D. White. 1993. Price and Concentration in Hospital Markets: The Switch from Patient-Driven to Payer-Driven Competition. *Journal of Law and Economics* 36(1):179-204.

Eakin, B. Kelly. 1991. Allocative Inefficiency in the Production of Hospital Services. *Southern Economic Journal* 58(1):240-248.

Ellison, Sara Fisher, and Christopher M. Snyder. 2010. Countervailing Power in Wholesale Pharmaceuticals. *The Journal of Industrial Economics* 58(1).

Feldstein, Paul. 1988. *Health Care Economics*. Third edition. New York: Wiley.

Ford, Jon M., and David L. Kaserman. 1993. Certificate-of-Need Regulation and Entry: Evidence from the Dialysis Industry. *Southern Economic Journal* 59(4):783-791.

Fournier, Gary M., and Yunwei Gai. 2007. What does Willingness-to-Pay reveal about hospital market power? FSU Working paper.

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

Gowrisankaran, Gautam, Aviv Nevo, and Robert Town. 2013. Mergers When Prices are Negotiated: Evidence from the Hospital Industry. NBER Working Papers 18875. National Bureau of Economic Research, Inc. Available at http://www.nber.org/papers/w18875.

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

Havighurst, Clark. 2005. Monopoly is Not the Answer. *Health Affairs* pp. 373-375.

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

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

McFadden, Daniel. 1997. Computing Willingness-to-Pay in random utility models. In *Trade, Theory and Econometrics: Essays in Honor of John S. Chipman*, edited by James C. Moore, Raymond Riezman, and James R. Melvin. New York, NY: Routledge, pp. 253-274.

_______________. 1998. Measuring Willingness-to-Pay for Transportation Improvements. In *Theoretical Foundations of Travel Choice Modeling*, edited by Tommy Garling, Thomas Laitila, and Kerstin Westin. Amsterdam: Elsevier Science, pp. 339-364.

Melnick, Glenn A, Jack Zwanziger, Anil Bamezai, and Robert Pattison. 1992. The effects of market structure and bargaining position on hospital prices. *Journal of Health Economics* 11(3):217-233.

_____________, and Emmett Keeler. 2007. The effects of multi-hospital systems on hospital prices. *Journal of Health Economics* 26(2):400-413.

Moriya, Asako S., William B. Vogt, and Martin Gaynor. 2010. Hospital prices and market structure in the hospital and insurance industries. *Health Economics, Policy and Law* 5:459-479.

Salkever, David, and Thomas Bice. 1976. The Impact of Certificate-of-Need Controls on Hospital Investment. *Milbank Quarterly* 54(2):185-214.

Sloan, Frank A. 1982. Government and the Regulation of Hospital Care. *American Economic Review* 72(2):196-201.

Spence, A Michael. 1973. Time and Communication in Economic and Social Interaction. *The Quarterly Journal of Economics* 87(4):651-60.

Staten, Michael, John Umbeck, and William Dunkelberg. 1988. Market share market power revisited: A new test for an old theory. *Journal of Health Economics* 7(1):73-83.

Town, Robert, and Gregory Vistnes. 2001. Hospital competition in HMO net-works. *Journal of Health Economics* 20(5):733-753. Available at http://ideas.repec.org/a/tpr/restat/v54y1972i2p195-98.html.

Endnotes

1. The track record of the applicant often plays a main role in the process. Applicants' experience, expertise in the line of business, accreditation, quality of existing firms and connection with the regulatory authority can "create a favorable impression or, more precisely, affect the agency's subjective probabilistic belief"(Spence (1973). This partly explains why incumbent hospitals are more likely to be granted the CON since they have more experience in the local market and have more information about the local community. Sloan (1982) conjectured that hospitals may apply for the CON without a credible intention to invest, but rather to prevent their competitors from doing so.

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

3. In their appendix, Capps et al. (2003) 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 health insurance markets. Moreover, we are not allowing the possibility that hospitals might use MCOs to their bargaining advantage. For a more complete analysis, see Dranove, Satterthwaite and Sfekas (2011) and Gowrisankaran, Nevo and Town (2013).

4. 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).

5. 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.

6. See Section 408.034 and 408.035 of Florida Statutes.

7. The 10 diagnostic categories are: 14 Cerebrovascular; 89 Pneumonia; 96 Bronchitis; 127 Heart Failure; 174 GI hemorrhage; 182 esophageal/gastric digestive disease with complications/comorbidities (cc); 183 same without cc; 243 Back problems; 296 Nutritional/metabolic disorders with cc; 320 Kidney/UTI with cc.

8. The present study has the advantage of using discharge data from more recent years, 2002 to 2005; consequently instead of average discount rates for all patients, we can use a more accurate measure of the discount rate for private pay patients only. Ideally, one would like to use, as a measure of hospital prices, the actual payment for each patient by private insurers and managed care organizations. But data the actual prices paid for patient care are not generally available, and this alternative measure is often used as a rough estimate.

9. These diagnostic categories are defined the same as in Keeler et al. (1999) and Melnick and Keeler (2007): diagnostic categories treated by the largest number of hospitals in the state. The reason for this “most widely treated” approach was to capture patients in diagnostic categories that could be given hospital care without specialized professionals or equipment and could be served by most community hospitals.

10. As a robustness test, we select diagnostic categories ranked by the largest discharge frequency in the state. We eliminated 11 DRGs from the top-50 DRGs with the “largest discharge frequency" that were not present in the discharge records of the 7 local hospitals, leaving 39 diagnostic categories.

11. We eliminated 3 diagnostic categories from the top-50 ‘most widely treated" DRGs that were not present in the data and 9 from the top-50 diagnostic categories with the “largest discharge frequency."

12. 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.

13. Specifically, Baptist Medical Center, St. Vincent’s Medical Center, Baptist Medical Center-Beaches, Shands Jacksonville Medical Center, Memorial Hospital Jacksonville, and St. Luke’s Hospital. In the St. Vincent application, the adjusted net revenue per discharge for private pay patients by St. Vincent is much less than Baptist ($5541.13 vs. $6769.69). The net revenue is based on inpatient data for 2004, adjusted for the severity of case mix. St. Vincent did not provide details for the data nor its methodology and no confidence intervals are provided. Since its claim contradicted similar calculations by the Agency for Healthcare Administration (AHCA) did not consider price differences a main factor in the decision making process.

14. The population in Clay County is growing at a greater rate (2.6%) than other neighboring counties (1.89%) and is projected to continue through 2010. The U.S. Census Bureau identified Clay County as the 49th fastest growing U.S. Counties by percentage growth from July 1, 2003 to July 1, 2004. The two main hospitals, Orange Park and St. Vincent, serving Clay County have an average of 72% occupancy rate in 2004 and over 90% during the peak admission seasons.

15. Attributes for the new hospital can be found in the application material submitted to AHCA.

16. Details about the market definition are provided in the appendix.

17. As our discussion on section 3 shows, when a new Baptist-affiliated hospital enters, the additional value of each existing hospital decreases while the joint value of Baptist and BMC Clay increases and becomes larger than the sum of the two hospitals separate WTPs absent co-ownership.

18. This pattern of results is further robust to the diagnostic category samples used to construct regressions and index weights, e.g. substituting the top-10 statewide weights or using the “most widely treated" DRGs.

19. Recommended Order, Case No. 06-0555CON, page 137. http://www.doah.state.fl.us/internet/. Accessed on April 8, 2009
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Tables

1. **Hospital Control Type and Services Offered in the Sample**

Hospital Name	City	County	Control	teaching	mri	cardio	nerv	resp	labor	psych	transplant
Shands Jacksonville Medical Center	Jacksonville	Duval	NFP	1	1	1	1	1	1	1	1
Florida Hospital	Orlando	Orange	NFP	0	1	1	1	1	1	1	0
Halifax Medical Center	Daytona Beach	Volusia	Gov	0	1	1	1	1	1	1	0
Saint Vincent's Medical Center	Jacksonville	Duval	NFP	0	1	1	1	1	1	0	0
Florida Hospital Deland	Deland	Volusia	NFP	0	1	1	0	1	1	1	0
Florida Hospital Waterman	Tavares	Lake	NFP	0	1	1	1	1	1	0	0
Munroe Regional Medical Center	Ocala	Marion	NFP	0	0	1	1	1	1	0	0
Shands at AGH	Gainesville	Alachua	NFP	1	1	1	1	1	1	1	1
Leesburg Regional Medical Center	Leesburg	Lake	NFP	0	1	1	0	1	1	0	0
Baptist Medical Center	Jacksonville	Duval	NFP	0	1	1	1	1	1	1	0
Shands at Lake Shore	Lake City	Columbia	NFP	0	1	0	0	1	1	0	0
Shands at Starke	Starke	Bradford	NFP	0	1	0	0	1	0	0	0
Shands Hospital at The Univ. Of Florida	Gainesville	Alachua	NFP	1	1	1	1	1	1	1	1
Baptist Medical Center - Beaches	Jacksonville Beach	Duval	NFP	0	1	0	0	1	1	0	0
Florida Hospital Flagler	Palm Coast	Flagler	NFP	0	1	1	0	1	0	0	0

Hospital Name	City	County	Control	teaching	mri	cardio	nerv	resp	labor	psych	transplant
Baptist Medical Center - Nassau	Fernandina Beach	Nassau	NFP	0	1	0	0	1	1	0	0
Saint Luke's Hospital	Jacksonville	Duval	NFP	0	1	1	1	1	1	0	1
Lake City Medical Center	Lake City	Columbia	FP	0	1	1	0	1	0	0	0
Florida Hospital - Ormond Memorial	Ormond Beach	Volusia	NFP	0	1	1	1	1	1	0	0
Memorial Hospital Jacksonville	Jacksonville	Duval	FP	0	1	1	0	1	1	0	0
North Florida Regional Medical Center	Gainesville	Alachua	FP	0	0	1	1	1	1	0	0
Ocala Regional Medical Center	Ocala	Marion	FP	0	1	1	0	1	1	0	0
Flagler Hospital	Saint Augustine	St. Johns	NFP	0	1	1	0	1	1	1	0
Orange Park Medical Center	Orange Park	Clay	FP	0	1	1	1	1	1	1	0
Putnam Community Medical Center	Palatka	Putnam	FP	0	1	1	0	1	1	0	0
Largo Medical Center	Largo	Pinellas	FP	0	1	1	1	1	0	0	0
Proposed Baptist Medical Center Clay	Orange Park	Clay	NFP	0	1	1	0	1	0	1	0
Proposed Orange Park South Clay Medical Center	Orange Park	Clay	FP	0	1	1	0	1	1	0	0
Proposed St. Vincent's Clay County	Orange Park	Clay	NFP	0	1	1	0	1	1	0	0

Note: Control indicates Not-for-Profit (NFP), Government (Gov) or for-profit (FP) ownership. The columns indicate whether the hospital is a teaching hospital and whether it offers services or specializes in magnetic resonance imaging (mri), cardiac care (cardio), diseases of nervous system (nerv), respiratory (resp), labor and delivery (labor), psychiatric care (psych) and organ transplant services (transplant).

2. Patient Sample Statistics in the CON application in 2005

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
age	56.821	24.917	urinary	0.047	0.211
lstay	4.866	7.099	endor	0.032	0.176
male	0.417	0.493	liver	0.028	0.166
white	0.781	0.414	genital	0.035	0.184
elderly	0.545	0.498	integ	0.022	0.147
child	0.090	0.286	infection	0.031	0.173
admission	1.845	0.991	injury	0.012	0.109
status	0.098	0.592	blood	0.013	0.113
fp	0.238	0.426	ent	0.009	0.092
teaching	0.112	0.315	alcohol	0.003	0.058
time	18.214	14.905	myelop	0.008	0.087
income	20.888	7.092	healthf	0.003	0.058
xchrlson	2.790	2.184	hiv	0.002	0.044
ndx	5.644	3.045	trans	0.001	0.026
npx	0.964	1.729	image	0.083	0.276
cardio	0.228	0.419	other	0.003	0.058
resp	0.110	0.313	medicare	0.522	0.500
labor	0.135	0.341	medcarhm	0.038	0.191
digest	0.095	0.293	commins	0.036	0.187
muscl	0.089	0.285	commhmo	0.196	0.397
nerv	0.069	0.254	commppo	0.208	0.406
psych	0.025	0.157			

3. Log Net Price Regressions Based on Alternative Diagnostic Categories

Variable	Widely Treated DRGs Statewide		DRGs of Highest Frequency Statewide		Widely Treated DRGs Locally		DRGs of Highest Frequency Locally		Keeler 10 DRGs
	Top 50	Top 10	Top 50	Top 10	Top 50	Top 10	Top 50	Top 10	
constant	6.912[a]	6.675[a]	7.88[a]	7.643[a]	6.595[a]	7.387[a]	7.875[a]	7.579[a]	6.223[a]
	(0.18)	(0.131)	(0.118)	(0.097)	(0.117)	(0.076)	(0.113)	(0.082)	(0.11)
Shands	-0.117	-0.174[a]	0.05	0.089[a]	0.034	0.17[a]	0.072	0.133[a]	-0.088
	(0.085)	(0.058)	(0.048)	(0.031)	(0.05)	(0.033)	(0.046)	(0.028)	(0.055)
St Vincent	-0.363[a]	-0.338[a]	-0.241[a]	-0.154[a]	-0.26[a]	-0.24[a]	-0.229[a]	-0.149[a]	-0.334[a]
	(0.066)	(0.042)	(0.04)	(0.031)	(0.037)	(0.024)	(0.038)	(0.027)	(0.048)
Baptist	-0.316[a]	-0.333[a]	-0.224[a]	-0.171[a]	-0.232[a]	-0.272[a]	-0.195[a]	-0.13[a]	-0.287[a]
Downtown	(0.063)	(0.037)	(0.033)	(0.017)	(0.036)	(0.024)	(0.031)	(0.014)	(0.047)
Baptist	-0.252[a]	-0.247[a]	-0.187[a]	-0.125[a]	-0.254[a]	-0.264[a]	-0.185[a]	-0.115[a]	-0.28[a]
Beaches	(0.085)	(0.047)	(0.059)	(0.048)	(0.048)	(0.033)	(0.056)	(0.043)	(0.06)
St Luke	0.27[a]	0.238[a]	0.278[a]	0.288[a]	0.206[a]	0.266[a]	0.274[a]	0.303[a]	0.209[a]
	(0.081)	(0.058)	(0.048)	(0.035)	(0.044)	(0.031)	(0.045)	(0.031)	(0.059)
Memorial	-0.191[a]	-0.175[a]	-0.147[a]	-0.116[a]	-0.149[a]	-0.189[a]	-0.143[a]	-0.113[a]	-0.228[a]
	(0.071)	(0.047)	(0.043)	(0.032)	(0.04)	(0.026)	(0.041)	(0.028)	(0.054)
Yr2003	-0.03	-0.026	-0.051[b]	-0.052[a]	-0.044[c]	-0.037[b]	-0.053[b]	-0.051[a]	-0.028
	(0.044)	(0.026)	(0.022)	(0.012)	(0.026)	(0.018)	(0.021)	(0.011)	(0.033)
Yr2004	0.043	0.024	0.015	0.006	0.018	0.024	0.012	0.006	0.044
	(0.044)	(0.027)	(0.022)	(0.012)	(0.025)	(0.018)	(0.021)	(0.011)	(0.033)
Yr2005	0.05	0.024	0.025	0.011	0.03	0.04[b]	0.021	0.009	0.067[b]
	(0.045)	(0.027)	(0.023)	(0.013)	(0.025)	(0.018)	(0.021)	(0.011)	(0.034)

[a] p-value .01 or less; [b] p-value .05 or less; and [c] p-value .1 or less

Parameter standard errors are given in parenthesis.

4. Proposed Service Areas and OPMC's Primary Service Area

CON 9872 BMC Clay	CON 9873 OPMC Clay	CON 9874 SVMC Clay	Existing Facility OPMC
32003	32003	32003	32003
32006	32092	32656	32244
32030	32656	32043	32210
32043	32043	32065	32043
32050	32091	32068	32065
32065	32065	32073	32068
32067	32259		32073
32068	32068		
32073	32177		
32079			

The joint 16 zip codes are: 32003 32006 32030 32043 32050 32065 32067 32068 32073 32079 32092 32091 32259 32177 32244 32210.

Source: CON#9872, 9873, 9874

Addresses of Proposed Hospitals:

BMC Clay: 2233 Village Square Pkwy Orange Park, FL 32003

SVMC Clay: 1850 Blanding Blvd Middleburg, FL 32068-3838, US

OPMC Clay: 801 Oak St Green Cove Springs, FL 32043, US

5. Aggregate Patients Utility After Introducing New Hospitals

Bootstrap	Existing Facility	Adding BMC Clay Utility	Adding BMC Clay % Increase	Adding OPMC Clay Utility	Adding OPMC Clay % Increase	Adding SVMC Clay Utility	Adding SVMC Clay % Increase
1	-32004.12	-24755.21	29.28	-26719.22	16.51	-23585.18	26.31
2	-30937.78	-22720.73	36.17	-28737.75	7.11	-22865.71	26.09
3	-30790.81	-23774.44	29.51	-27278.46	11.41	-23876.40	22.46
4	-32804.31	-24869.09	31.91	-28657.63	12.64	-24507.80	25.29
5	-32119.15	-23797.96	34.97	-27330.10	14.91	-24912.68	22.44
6	-32246.08	-23279.97	38.51	-28210.63	12.51	-24230.19	24.86
7	-32360.40	-23472.81	37.86	-27287.03	15.68	-22503.81	30.46
8	-31968.47	-22180.19	44.13	-28647.10	10.39	-24482.62	23.42
9	-30969.92	-24329.19	27.3	-28109.16	9.24	-23749.94	23.31
10	-32265.14	-22175.93	45.5	-28445.92	11.84	-24388.35	24.41
–	–	–	–	–	–	–	–
100	-32244.68	-24669.63	30.71	-27255.80	15.47	-24023.94	25.49
Mean	-31737.11	-23675.26	34.2	-27645.96	12.84	-23903.17	24.66
Std. Dev.	712.38	792.62	5.3	777.22	3.36	744.21	2.46

6. Predicted Price Change after Introducing a New Hospital

	Hospital	DRGs with Highest Frequency Locally						Keeler et al(1999)		
		Top 50			Top 10			Top 10		
Scenario 1:	BMC Clay	Price Change	District Four	Service Area	Price Change	District Four	Service Area	Price Change	District Four	Service Area
	Shands	-0.75	-0.049	-0.034	-0.941	-0.061	-0.043	-0.692	-0.045	-0.032
	St Luke	-1.357	-0.142	-0.081	-1.766	-0.185	-0.106	-1.299	-0.136	-0.078
	Memorial	0.128	0.017	0.007	0.161	0.021	0.009	0.118	0.016	0.007
	St Vincent	-1.338	-0.256	-0.298	-1.677	-0.321	-0.373	-1.234	-0.236	-0.275
	Baptist Downtown	1.255	0.448	0.314	1.577	0.563	0.395	1.155	0.413	0.289
	Baptist Beaches	-0.116	-0.008	0	-0.141	-0.009	0	-0.124	-0.008	0
	Orange Park	-8.759	-0.726	-3.177	-11.059	-0.916	-4.011	-8.242	-0.683	-2.989
	Weighted Price Change		-0.715	-3.27		-0.908	-4.13		-0.68	-3.078
Scenario 2:	OPMC Clay	Top 50			Top 10					
	Shands	-0.929	-0.06	-0.043	-1.165	-0.076	-0.053	-0.857	-0.057	-0.045

	St Luke	-1.91	-0.2	-0.114	-2.483	-0.26	-0.149	-1.829	-0.195	-0.123
	Memorial	-1.016	-0.134	-0.057	-1.275	-0.168	-0.072	-0.937	-0.127	-0.063
	St Vincent	-1.47	-0.281	-0.327	-1.843	-0.353	-0.41	-1.356	-0.265	-0.298
	Baptist Downtown	-1.914	-0.683	-0.479	-2.397	-0.856	-0.6	-1.765	-0.513	-0.27
	Baptist Beaches	-0.145	-0.01	0	-0.176	-0.012	0	-0.155	-0.01	0
	Orange Park	7.686	0.637	2.788	9.929	0.823	3.601	7.195	0.831	3.146
	Weighted									
	Price Change		-0.732	1.767		-0.901	2.317		-0.336	2.346
Scenario 3:	SVMC Clay		Top 50			Top 10				
	Shands	-0.918	-0.06	-0.042	-1.152	-0.075	-0.053	-0.846	-0.054	-0.037
	St Luke	-0.876	-0.092	-0.052	-1.14	-0.119	-0.068	-0.838	-0.084	-0.044
	Memorial	-0.215	-0.028	-0.012	-0.27	-0.036	-0.015	-0.198	-0.026	-0.01
	St Vincent	0.905	0.173	0.201	1.137	0.218	0.253	0.833	0.235	0.302
	Baptist Downtown	-0.176	-0.063	-0.044	-0.221	-0.079	-0.055	-0.162	-0.045	-0.017
	Baptist Beaches	-0.157	-0.011	0	-0.19	-0.013	0	-0.168	-0.011	0
	Orange Park	-8.212	-0.68	-2.979	-10.376	-0.86	-3.763	-7.726	-0.621	-2.972
	Weighted									
	Price Change		-0.76	-2.928		-0.963	-3.702		-0.607	-2.778

Figure 1. Hospital market area construction for the CON case

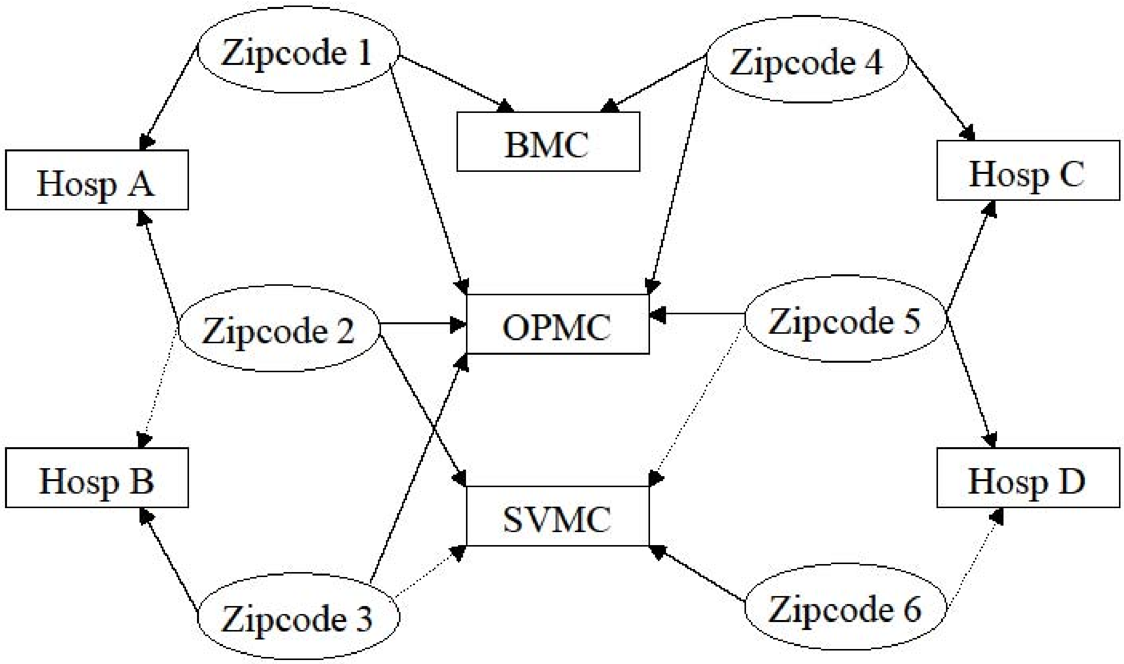
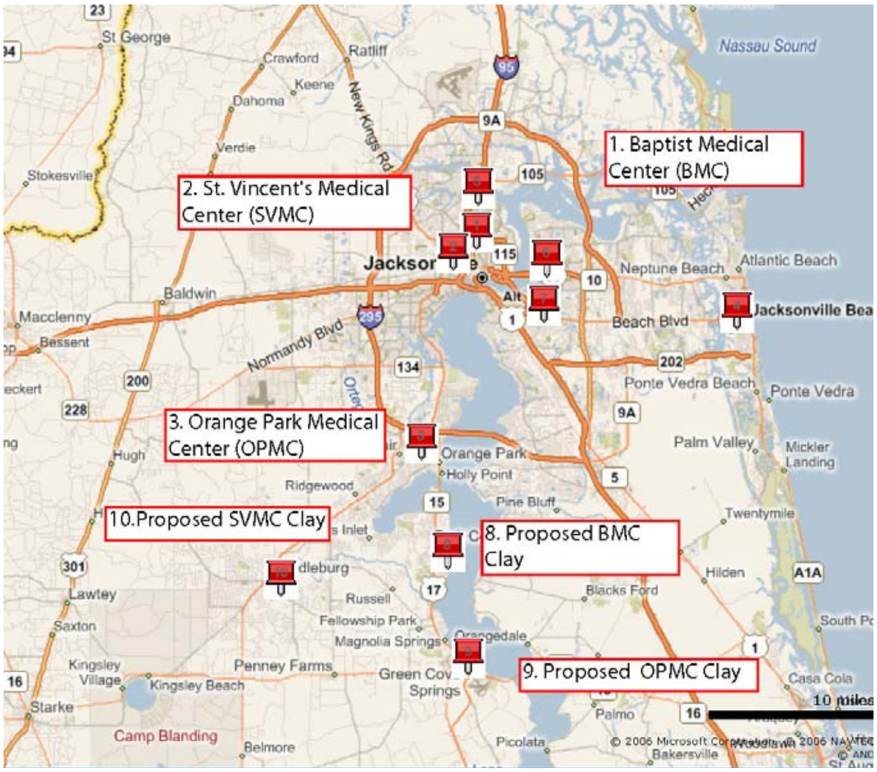


Figure 2. Locations of the 7 main hospitals and 3 proposed new hospitals in the CON case.



1. Baptist Medical Center (BMC)
2. St. Vincent’s Medical Center (SVMC)
3. Orange Park Medical Center (OPMC)
4. Baptist Medical Center – Beaches
5. Shands Jacksonville Medical Center (Shands)
6. Memorial Hospital Jacksonville
7. St. Luke’s Hospital
8. Proposed Baptist Medical Center of Clay (BMC Clay)
9. Proposed Orange Park South Clay Medical Center (OPMC Clay)
10. Proposed St. Vincent’s Clay County (SVMC Clay)

Appendix 1: Data and Variables

The main hospitals in the local area for this study are the three applicants for the CON to build a new hospital in Clay County, Baptist Medical Center (BMC), Orange Park Medical Center (OPMC), and St Vincent's Medical Center (SVMC), and 4 other hospitals in the area, i.e. Health Planning District 4 including Baker, Clay, Duval, Nassau and St. Johns Counties. Figure 2 is a map of these hospitals including the proposed new ones.

Inpatient discharge data and hospital financial data from 2002 to 2005 are collected from Florida Agency for Health Care Administration (AHCA). Patient characteristics in the data include detailed clinical and demographic information. Patients' diagnoses and procedures are coded in Diagnosis Related Groups (DRG) which are aggregated up to Major Diagnosis Codes (MDCs). Also included are the patient's length of stay, payer category (Medicare, Medicaid, HMO, PPO etc.), demographics (age, race, sex etc.), and patient residential zip code location. Attributes of each hospital include its control type (for profit, not for profit, or government), teaching status, nursing intensity, capital intensity, and an inventory of services offered.

Patient income data by race and zip code for 2000 are from US Census 2000 Summary File 3 (SF 3) - Sample Data at http://www.census.gov/main/www/cen2000.html. The travel time from patient's home to each hospital is estimated from www.mapquest.com.

It must be noted at the outset that the sampling design is subject to certain considerations. We use the choice based sampling strategies to select relevant hospitals and patients and to construct zip code specific choice sets. Consistent with patient flow 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 local hospitals. Second, the data set should include substantially all of the patients that received services from the local hospitals, without restricting those patients by how far away they reside from the hospital. In short, 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 illustrates, in principle, how the market is defined. The three boxes in the middle represent the three applicants. First, identify all the zip codes for the patients who were discharged from these three hospitals. In this example, patients from zip codes 1, 2, 3, 4, 5 and 6 received care at the three 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 hospitals A, B, C and D. Some zip codes were excluded if very small numbers of patients were drawn to the three local hospitals (note the dotted line in figure 1).

In the final sample, we have 439,076 patients from 67 zip codes and 26 hospitals (including the 7 main hospitals). We are able to cover 88.07% (131922 out of 149799) of patients discharged from the 7 existing hospitals (3 local hospitals currently owned by the CON applicants plus 4 other hospitals in District 4). Table 1 lists the 26 hospitals in the sample, including their control types and services offered.

While we can readily determine the actual choices patients make in the data, we cannot identify for certain the exact choice set for each patient. For instance, if an HMO payer restricts 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 they are constructed for Medicare patients or 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 this method would identify the union of all HMO choices.

Information for the three proposed new hospitals comes from the application material and show differences in the range of services they plan to offer. The proposed BMC Clay, OPMC Clay and SVMC Clay offer services in magnetic resonance imaging, cardiac care, respiratory system disorder. None of the three proposed hospitals have organ transplant services or neurological surgeries. While OPMC Clay and SVMC Clay offer obstetric care, BMC Clay does not include obstetric care in the proposal; unlike the others, BMC Clay offers psychiatric care services. The three proposed hospitals also differ in their locations, which are shown in figure 2. Descriptive statistics on the patient discharge sample are included in table 2.