1 Introduction

There is keen interest in estimating empirical models of economic behavior in order to derive predictions that can be useful for strategic analysis and antitrust. The economic theories that form the foundation for empirical estimation often assume that agents are rational and act with foresight.\(^1\) In many models, fully rational agents not only calculate the immediate impact of their economic decisions, but through a repeated feedback loop leading to a fixed point must also account for how those decisions affect the decisions of other players and themselves. This sophisticated thinking is the essence of non-cooperative game theory

\(^1\)For example, the chainstore paradox, which requires considerable foresight, fuels skepticism over whether firms can profit by predatory pricing.
and its most popular solution concepts: Nash equilibrium for static settings and subgame perfect Nash equilibrium for dynamic settings. These models, while enormously attractive theoretically, may well leave one wondering to what degree economic agents really act with rational foresight.

Theorists and experimentalists have reacted to this credibility gap by developing and testing models of bounded rationality. Within game theory, with its demands for taking into account other agents’ reactions, one of the most successful has been the “cognitive hierarchy” or “k-level thinking” model that Stahl and Wilson (1994, 1995) and Nagel introduced and that Camerer, Ho, Chong (2004), Crawford and Iriberri (2007), and many others have since developed. Under level $k$-level thinking, a characteristic of each agent is how far ahead he can think. In laboratory experiments, while a few agents may not be able to think ahead, most agents are able to think one, two, three, or more steps ahead. For example, in hide-and-seek if you are hiding and I am searching for you, I might guess that you will hide in the closet under the stairs, but then decide to look elsewhere because I think you will realize that I will think you will hide there.

Using field data to measure what degree of foresight agents bring to interactive economic situations is difficult and, as a consequence, there are not a large number of examples. One recent example, which uses data from a popular Swedish lottery game, is Östling, Wang, Chou et al (2011) It shows that participants strategies are quite close to the mixed Nash equilibrium strategies. Certain significant discrepancies between the data and the predictions of equilibrium, however, can be rationalized with a $k$-level, cognitive hierarchy model.

In this paper we examine whether hospitals and insurers show rational foresight when bargaining over prices. Our interest in this market has two sources. First, it is a market with rich enough data that we can investigate the degree to which economic organizations in a complicated, high stakes environment are forward looking. Second, and equally important, the hospital and health insurance industries are of enormous public policy significance. This
work, which should be regarded as exploratory because of the limited number and size of the markets we analyze, provides evidence on what dimensions the this market performs well and what dimensions it performs not so well.

This paper is an extension of Capps, Dranove, and Satterthwaite (2003, CDS hereafter) that has been used in a number of antitrust analyses.\(^2\) CDS set out a method to quantify the consumer surplus that a particular hospital brings to a network put together by a managed care organization (MCO). The key innovation in CDS is the development of the expression for willingness to pay (WTP) that measures, in utils the consumer surplus that a hospital brings to a network. CDS show that WTP is a powerful predictor of hospital profits. An important limitation of CDS is that neither the MCO nor the hospital display foresight; they do not consider how their negotiations will affect the MCO’s negotiations with other hospitals. In particular, when a hospital and MCO fail to agree on a price and the hospital is excluded from that MCO’s network, its absence then imposes externalities on the remaining hospitals and therefore may alter the outcomes of the MCO’s negotiations—often adversely—with them. A hospital, realizing this, may successfully demand a higher price for its services because an impasse in the bargaining resulting in its exclusion from the network is more costly to the MCO than if the equilibrium reimbursement rates were not interrelated. In other words, foresight may give individual hospital’s some bargaining leverage. CDS ignore this leverage.

We measure bargaining leverage by adapting a key insight of the Stole & Zwiebel (1996; henceforth SZ) model of employer/employee bargaining. SZ address the question of how the departure of one worker increases the bargaining power of the remaining workers. The parallel to hospital markets is direct: if an insurer drops a hospital from its network, the

\(^2\)The bargaining concept developed by CDS was invoked by the FTC’s expert in the ENH hospital case and the CDS method was used by the plaintiff’s expert in a class action claim against ENH; the FTC expert used a variant of CDS to analyze a merger in Virginia, and the plaintiff’s expert in an Illinois case involving alleged monopolization used the CDS methodology to define the geographic market.
remaining hospitals may increase their bargaining power.

We make two important modifications to SZ. First, we introduce “levels of rationality,” which is similar but not identical to $k$-level thinking. SZ assume that firms and workers are fully rational, i.e. they consider all possible configurations of employees that could be hired by the firm. We argue that neither hospitals nor the MCO can perform—or would be willing to act on—the extremely complex calculations necessary for the fully rational SZ bargaining solution. Instead we posit that bargainers are forward-looking to a limited extent and we use the data to determine how far forward they look. We consider two levels of rationality. In level 0 rationality, managers in both the MCO and each hospital $X$ naively bargain over the split of the “direct” marginal value the hospital adds to the proposed network. In level 1 rationality, the MCO and hospital $X$ in their bilateral negotiations also account for the “indirect” effects that a breakdown of their negotiations and consequent exclusion from the network has on $X$’s marginal value to the network. In particular, if $X$ is no longer in the network, then the patients that $X$ would have cared for now go to another, perhaps higher cost hospital. Additionally, without $X$ in the network, the remaining hospitals may have increased bargaining power vis-a-vis the MCO and therefore be able to increase their negotiated payment rates when their contract expires. Our idea is that if the negotiators are naive they will bargain with level 0 rationality while if they are reasonably sophisticated they will look one step down the game and bargain with level 1 rationality.

Our second modification is that we introduce an attenuation parameter, $\rho$, that allows us to capture the possibility that bargainers do not fully account for the impact of leverage. This may simply reflect a degree of bounded rationality somewhere between level 0 and level 1. However, it may also reflect institutional realities. Specifically, if a hospital $Y$ and a MCO have a contract that runs for several years, then the leverage that hospital $X$ potentially possesses due to why renegotiating its rates may not materialize for two or three years during which time market conditions may have changed in unpredictable ways. This suggests that the negotiators on both sides of the table may, depending on the specific
circumstances, discount the bargaining leverage our model identifies.

The plan of the paper is as follows. After first describing the institutional environment of hospital/MCO negotiations, we derive the bargaining solution for our modified model with level 1 rationality. This generates both precise measures of leverage and a nonlinear structural equation relating leverage to revenues. We empirically test for the importance of leverage by estimating both reduced form OLS and structural nonlinear least squares regressions. Using data on hospitals in four metropolitan areas in California, we find that leverage is large in magnitude but imprecisely estimated in OLS specifications. When we estimate the structural nonlinear least squares specification, leverage becomes statistically significant, though smaller in magnitude. We use our results to simulate the impact of several hypothetical mergers on hospital prices. We find that predicted price changes that account for leverage are smaller than predictions derived from a simpler empirical specification that only accounts for changes in WTP. Our results also suggest the need for better cost data; the volatility of some of our results may be traced to problematic cost estimates.

2 Background on Hospital Contracting and the Capps/Dranove/Satterthwaite Model

Most managed care organizations (MCOs) assemble provider networks in each metropolitan area in which they do business. A provider network consists of local hospitals, physicians, and other health care entities who have agreed to give discounted prices to the MCO. In exchange, the MCO gives its enrollees financial incentives to receive care from network providers. This usually takes the form of reduced copayments. In other words, hospitals give discounts in expectation of higher volume. Conversely, hospitals that fail to give a satisfactory discount may be excluded from a network and lose substantial volume. Based on our personal experience as well as information reported in Ho (2006), most urban hospitals
are in most MCOs’ networks.

MCOs assemble their hospital networks through direct negotiation. All major MCOs have negotiation specialists who deal with the hospitals in a market area. They negotiate directly with each hospital’s CFO (chief financial officer) or other high ranking executive. MCOs and hospitals usually negotiate multiyear contracts that include formulaic annual price increases. In the markets that we study—metro areas of California circa 1990—this process of selective contracting had been commonplace for nearly a decade. CDS use a logit demand framework to model the value that patients receive when a hospital is added to a network. They assume that patients select their network prior to realizing their medical needs. Patients value adding additional hospitals to a network because it gives them the option of visiting that hospital if they become ill and that hospital best meets their needs. An MCO’s willingness to pay (WTP) for including a hospital in a network is the sum of the valuations of each of its enrollees.

Because each patient (or employer acting as the patient’s agent) must choose an MCO and provider network prior to realizing her health states, the WTP for a hospital’s participation in the network depends on patients’ *ex ante* expectations of their likely health needs as well as the value of accessing that hospital to meet those needs. CDS develop an exact formula for WTP: it is a function of the hospital’s market shares in “micromarkets,” defined by location, illness, and patient demographic characteristics. Thus, a medium-size hospital that dominates maternity care in a suburban area may have higher WTP than a large urban hospital that does not have a dominant share in any particular locality or disease. CDS compute WTP from predicted market shares based on the results of a conditional choice model that includes hospital and patient characteristics as well as a rich set of interactions.

CDS assume that the mechanism by which WTP translates into the actual prices that MCO’s pay hospitals is a simplistic bargaining process. For example, suppose that there are three hospitals in a market, X, Y, and Z. CDS assume that when an insurer bargains with hospital
X, both the insurer and X assume that hospitals Y and Z are in the network. Thus, the insurer and hospital X bargain over the additional rents gained by including X and creating a “network of the whole.” These rents equal WTP minus the incremental cost of treating patients at X.

CDS fail to account for the fact that excluding a hospital from a network may affect the bargaining outcome with other hospitals. This can give each hospital some leverage that might allow it to negotiate more favorable rates. To illustrate the idea of leverage, consider hospitals X and Y that are located close to each other, offer almost the same menu of services, and have approximately the same reputations. Hospital X does not necessarily add very much to a network that already contains hospital Y and in the CDS formulation, the WTP for hospital X would be low. But the presence of hospital X in the network reduces the incremental surplus that hospital Y adds to the network, which harms hospital Y’s bargaining position. This gives “WTP leverage” to hospital X, and by contracting with X, the MCO prevents hospital Y from holding it up. Leverage may also apply to costs: if X is relatively more efficient than Y, then if X drops from the network, its erstwhile patients may instead choose hospital Y which may have negotiated higher rates. This provides some “cost leverage” to hospital X. On the other hand, if Y is more efficient than X, the MCO may be glad to remove X from the network. In this case the cost leverage is negative.

If hospitals and the MCO account for leverage, they may strike deals that are somewhat different than those predicted by CDS. Leverage may also be affected by mergers, which may be important for antitrust analysis. Our goal is to measure leverage, determine whether leverage affects pricing, and assess the implications for merger analysis.
3 Model

The SZ model of bargaining between employers and employees translates straightforwardly to fully rational bargaining between MCOs and their network hospitals. The MCO bargains with each hospital over whether the hospital will be included in the managed care network. The hospital’s value to the MCO comes from three sources: the value to consumers of being able to utilize that hospital with a low deductible and copayment, the reduction in bargaining power its presence imposes on the other hospitals in the network, and—provided the hospital is low cost—the decreased total cost of providing the hospital care the MCO’s consumer membership requires.

This is a high stakes market game that hospitals and insurers play repeatedly. Given its repeated nature and importance to all parties, we posit that both hospitals and the MCO have complete information concerning consumers’ WTP for networks with varying hospital memberships and the resulting costs of care. The total surplus the hospital brings to the network is the sum of consumers’ willingness-to-pay (WTP) for the hospital and the total reduction in payments to all other network hospitals. The hospital and the MCO bargain over how this surplus is divided up between them. We do not model the actual back and forth microstructure of the bargaining process. Rather, following Binmore, Rubinstein, and Wolinsky (1986), we assume that the MCO and each hospital bilaterally negotiate by playing an alternating offer game. The MCO or hospital after receiving an offer from its counterparty may accept the offer or make a counter-offer. With a small, positive (and exogenous) probability $\gamma$ the counterparty may refuse to consider the counter-offer. This risk that bargaining may reach an impasse at any point drives both parties towards agreement provided there are gains to be realized. As Binmore, Rubinstein, and Wolinsky. (1986) show, as the probability $\gamma$ approaches zero, the equilibrium outcome of this extensive form game approaches the axiomatic Nash (1953) bargaining solution. This need not involve a 50-50 split of the surplus; depending on their relative risk aversion and beliefs concerning
the probability $\gamma$ of breakdown the equilibrium split may be quite asymmetric.

Given this framework the key equation that defines the equilibrium revenue $R_i(B)$ that hospital $i$ receives from the MCO for participating in the network $B = \{1, 2, \ldots, N\}$ consisting of all $N$ hospitals in the market is this:

$$\frac{1}{\lambda} \{R_i(B) - C_i(B)\} = \frac{1}{1 - \lambda} \left\{ \alpha \Delta_i F(B) - R_i(B) + \rho \sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)] \right\}. \quad (1)$$

This is our “division” equation from which in the next section we derive the equation we use for estimating the parameters $\lambda$, $\alpha$, and $\rho$. The notation is as follows:

- $B$ is the full set of hospitals that are in the MCO’s network and $i$ represents a hospital in that network. $B \setminus i$ is the network $B$ with hospital $i$ excluded.

- $\lambda$ is the proportion of the surplus due to hospital $i$’s inclusion in the MCO’s network generates that hospital $i$ captures. Therefore $1 - \lambda$ is the proportion of the surplus that the MCO captures. The alternating offer bargaining game described above determines the value of $\lambda$.

- $R_i(B) = n_i(B) w_i(B)$ is hospital $i$’s total revenue from serving the $n_i(B)$ admissions at the reimbursement rate of $w_i(B)$ when the network is $B$. $R_j(B \setminus i) = n_j(B \setminus j) w_i(B \setminus j)$ is hospital $j$’s revenue when hospital $i$ is excluded from the network $B$. Observe that $n_i(\cdot)$ is a function only of the network’s membership; it does not depend on $w_i(\cdot)$ because we assume that the copayments and deductible for in-network care are small enough not to have an appreciable affect on consumers’ choices among hospitals.

- $C_i(B) = n_i(B) c_i(B)$ are the incremental costs hospital $i$ incurs from serving the $n_i(B)$ admissions it receives when the network is $B$. The marginal cost of hospital $i$ serving an additional patient is $c_i(B)$; it is constant, but may vary with with the network, i.e., $c_i(B) \neq c_i(B \setminus j)$.
\( \Delta_i V(B) = \alpha \Delta_i F(B) \) is the incremental WTP (in dollars), summed across all patients served by the MCO, that the hospital brings to the network. \( \Delta_i F(B) \) is the incremental WTP in utils and \( \alpha \) is the constant parameter that converts utils into dollars. \( V(B) \) is the total WTP of consumers for the network \( B \) and \( V(B \setminus i) \) is the total WTP of consumers for the network \( B \setminus i \). Therefore \( \Delta_i V(B) = V(B) - V(B \setminus i) \).

\( \rho \in [0, 1] \) is the attenuation factor that specifies the weight that the indirect surplus receives in determining equilibrium reimbursement rates. If \( \rho = 1 \), then the rate per admission, \( w_i(B) \) and resulting revenue \( R_i(B) \) that hospital \( i \) receives is level 1 rationality. If \( \rho = 0 \), then the rate \( w_i(B) \) and revenue \( R_i(B) \) is level 0 rationality.

The left-hand side of equation 1 is the surplus (i.e., profit) hospital \( i \) receives from the managed care patients.. On the right-hand side, the first term, \( \Delta_i V(B) - R_i(B) \), is the MCO’s direct surplus increase from including hospital \( i \) in its network; it is consumers’ WTP for hospital \( i \) less the amount the insurer pays \( i \). The second term,

\[
\sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)] = \sum_{j \in B \setminus i} [n_j(B \setminus i) w_j(B \setminus i) - n_j(B) w_j(B)],
\]

is the MCO’s indirect increase in surplus from including \( i \); it is the decrease in payments that the MCO makes to the other hospitals as a result of including \( i \). The attenuation parameter \( \rho \) recognizes that this latter term may be neglected in whole or part during the bilateral negotiation between hospital \( i \) and the MCO.

If \( \rho = 1 \) (negotiations at level 1 rationality) equation (1) follows directly from the formula for the incremental surplus that hospital \( i \) generates for distribution among the MCO and the hospitals in its network. Total surplus generated by the network \( B \) is \( V(B) \), consumers’ total WTP to have access to the network \( B \), less the total cost \( \sum_{j \in B} C_j(B) \) of providing the care that they consume. Therefore the incremental surplus that hospital \( i \) generates is:
\[
\Delta_i S(B) = \left[ V(B) - \sum_{j \in B} C_j(B) \right] - \left[ V(B \setminus i) - \sum_{j \in B \setminus i} C_j(B \setminus i) \right]
\]

\[
= \Delta_i V(B) - C_i(B) - \sum_{j \in B \setminus i} [C_j(B) - C_j(B \setminus i)]
\]

\[
+ (R_i(B) - R_i(B)) + \sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)] - \sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)]
\]

Terms that sum to zero

\[
= \Delta_i V(B) - R_i(B) + \sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)] + [R_i(B) - C_i(B)]
\]

MCO’s increase in surplus

\[
+ \sum_{j \in B \setminus i} [(R_j(B) - C_j(B)) - (R_j(B \setminus i) - C_j(B \setminus i))]
\]

Externality hospital i’s inclusion imposes on other hospitals

\[
= \Delta_i P(B) + \Delta_i E(B)
\]

where \(\Delta_i P(B)\) is the “private” surplus hospital \(i\) and the MCO create and \(\Delta_i E(B)\) is the “externality” surplus (likely cost) they impose on the other hospitals. If hospital \(i\) and the MCO negotiate with level 1 rationality, then they split \(\Delta_i P(B)\) with \(\lambda\) proportion going to \(i\) and \(1 - \lambda\) proportion going to the MCO; i.e. they jointly set \(R_i(B)\) to satisfy

\[
\frac{R_i(B) - C_i(B)}{\Delta_i V(B) - R_i(B) + \sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)] + [R_i(B) - C_i(B)]} = \lambda.
\]

Observe that in setting \(R_i(B)\) the MCO and hospital \(i\) ignore the externalities \(\Delta_i E(B)\) that they impose on the other hospitals in the network.

Before we transform the division equation (1) into the estimating equation we must discuss two crucial issues involving the indirect surplus \(\sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)]\) that hospital \(i\)’s inclusion creates. First, why does it make a sense to introduce the attenuation parameter \(\rho\)
to weight the indirect surplus within (1), the division equation? Second, the only revenues we observe in the data are $R_i(B)$ and $\sum_{j \in B \setminus i} R_j(B)$ because the data is the outcome of all hospitals in the market—the set $B$ of hospitals—participating in MCO networks. We do not observe the revenue $\sum_{j \in B \setminus i} R_j(B \setminus i)$ that would result if $i$ were banished from the market. How therefore should we, for each hospital pair $i, j \in B$, estimate $R_j(B \setminus i)$?

With respect to the first issue, level 0 rationality ($\rho = 0$), suppose the agreement between the MCO and hospital $i$ is about to expire and both parties believe that any breakdown in negotiations will be sufficiently short-lived so that each other hospital $j$ will not have an incentive to renegotiate their revenue to the level $R_i(B \setminus i)$ that would be an equilibrium if $i$ were to be permanently excluded from the network, i.e., both $i$ and the MCO believes that for this negotiation $w_j(B \setminus i) = w_j(B)$ for all hospitals $j \in B \setminus i$. Substituting these beliefs into the formula for $\Delta_i P(B)$ implies that the surplus to be split is:

$$\Delta_i P(B) = \Delta_i V(B) - w_i(B) n_i(B) + \sum_{j \in B \setminus i} w_j(B) [n_j(B \setminus i) - n_j(B)] + [(w_i(B) - c_i(B)) n_i(b)]$$

$$\approx \Delta_i V(B) - w_i(B) n_i(B) + wn_i(B) + [(w_i(B) - c_i(B)) n_i(b)]$$

$$= \Delta_i V(B) + wn_i(B) - C_i(B)$$

where (i) $w$ is the average rate that the MCO pays the other hospitals to care for the $n_i(B)$ patients that hospital $i$ would have cared for if it were not temporarily excluded from the network and (ii) $\sum_{j \in B \setminus i} [n_j(B \setminus i) - n_j(B)] = n_i(B)$ because $i$’s presence or absence in the network does not change, at least in the short run, the number of enrollees in the MCO’s health plan and the quantity of care they require. Further, the MCO has an incentive not to educate an unsophisticated hospital—a hospital that negotiates with level 0 rationality—that $wn_i(B)$ should be included in the splittable surplus $\Delta_i P(B)$. Therefore, for a level 0 rationality hospital, the equilibrium level of $R_i(B)$ satisfies the division equation (1) with
the attenuation parameter \( \rho \) set to 0:

\[
\frac{1}{\lambda} \{ R_i(B) - C_i(B) \} = \frac{1}{1 - \lambda} \left\{ \alpha \Delta_i F(B) - R_i(B) + \rho \sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)] \right\} \\
= \frac{1}{1 - \lambda} \left\{ \alpha \Delta_i F(B) - R_i(B) \right\}.
\]  

(3)

Increasing \( \rho \) from 0 to 1 represents increased sophistication on the part of the hospital (and perhaps also the MCO). Thus in this scenario in which both hospital \( i \) and the MCO believe that any impasse in the negotiations will be too short to induce other hospitals to renegotiate their rates from \( w_i(B) \) to \( w_i(B \setminus i) \), a sophisticated hospital (level 1 rationality) would insist that \( wn_i(B) \) be included in \( \Delta_i P(B) \), which would of course result in a higher, equilibrium reimbursement rate \( w_i(B) \) for itself.

Taking our analysis further, we now observe that hospital \( i \) and the MCO, if they are really sophisticated, will not have beliefs that an impasse will be so short that the other hospitals in \( B \) will not be able or have an incentive to renegotiate their revenue from \( R_i(B) \) to \( R_i(B \setminus i) \). Suppose that the indirect surplus term \( \sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)] \) is substantial and positive, and hospital \( i \) being quite sophisticated knows it. If the MCO does not acknowledge its existence and magnitude, then hospital \( i \) will surely reject all the MCO’s low ball proposals. The impasse will be permanent unless the MCO accepts that indirect surplus must be included if it wants a deal, which it surely does. And, if the impasse is permanent, the equilibrium negotiated revenue for each hospital \( j \in B \setminus i \) is \( R_j(B \setminus i) \). An exactly parallel argument applies if \( \sum_{j \in B \setminus i} [R_j(B \setminus i) - R_j(B)] \) is substantial and negative except that the MCO pushes for the hospital to acknowledge its existence. Thus, to summarize, a naive hospital (or a naive MCO) may not realize the importance the indirect surplus that a hospital’s inclusion creates. The negotiation over \( R_i(B) \) therefore occurs with level 0 rationality (i.e., with \( \rho = 0 \)). But if both the hospital and MCO are sophisticated, then the importance of the indirect surplus will be recognized and the negotiation will be with level 1 rationality (i.e., with \( \rho = 1 \)).

We now consider the second issue with respect to the indirect surplus. The terms \( R_j(B \setminus i) \)
in the division equation (1) represents the revenues of hospital $j$ when $i$ is excluded from
the network. The values of $R_j (B \setminus i)$, for all hospital pairs $i, j \in B$, play an essential role
in determining the equilibrium vector of revenues $(R_1 (B), \ldots, R_i (B), \ldots, R_N (B))$ for the
hospitals in the market. If the hospitals in the market had unbounded rationality (i.e.,
level $\infty$ rationality), then, as with the equilibrium determination of $R_i (B)$, hospital $j$’s
revenue $R_j (B \setminus i)$ when hospital $i$ is excluded from the network depends on the equilibrium
revenue $R_k (B \setminus i, j)$ of hospital $k \in B \setminus i, j$ when both hospitals $i$ and $j$ are excluded from
the network. Logically this induction continues through several rounds until all hospitals
except one are excluded from the network.\(^3\) Pursuing this induction down more than one
level seems unreasonable to us for two reasons.

First, hospital networks for managed care in any but the smallest markets must have several
hospitals at a minimum to be viable. Ex ante every consumer values choice among hospitals
because each hospital has unique strengths and weaknesses that affect its attractiveness after
the consumer learns the nature of the health problem he or she faces. Thus for a routine
surgical procedure a consumer may prefer the nearby community hospital while for a brain
tumor he may willingly travel across the city to the hospital with the best neurosurgery
team. These preferences drive a result of CDS (2003, Appendix B) that, in general, MCOs
prefer their network to be the network-of-the-whole. An implication of this result is that
a small network, except in very special circumstances, will not be sufficiently attractive in
terms of cost and choice to survive against competing, large networks. Thus rates for small
networks are undefined because such networks are infeasible.

Second, and more importantly, is the immense complexity that the MCO and hospitals
face in trying to pursue the induction logic to its endpoint. Large metropolitan areas have
substantial numbers of hospitals. A small market might have five hospitals, a medium
sized market might have fifteen hospitals, and a large market might have thirty or more

\(^3\)This induction is central to the solution that Stole and Zweibel (1996) derive for their intrafirm wage
bargaining problem.
hospitals. To pursue the induction logic to its logical end the MCO and hospitals in the
market must be able to predict for each possible subnetwork \( B' \subset B \) the WTP \( \Delta_i V (B') \)
for each hospital \( i \in B' \). While they may have a good idea of where one hospital’s patients
would go if that hospital left the network, they would have a much harder time predicting
where patients would go if two or more hospitals left the network, etc. Further, even if the
bargainers can derive useful estimates of the necessary WTPs to complete the induction, the
calculations required to compute the equilibrium revenues \( R_i (B') \) for all \( B \subset B \) and all \( i \)
explodes exponentially. Specifically, if the induction is carried to its logical end, the number
of equations that must be solved simultaneously to obtain the full set of \( R_i (B') \) values goes
from 80 for a five hospital market to 16 million for a thirty hospital market. Given these
issues, we think it is reasonable to assume that bargainers ignore leverage effects beyond one
level.

Specifically, we determine values for \( R_j (B \setminus i) \) that are needed to solve the division equation
(1) with a level 0 rationality version of it:

\[
\frac{1}{\lambda} [R_j (B \setminus i) - C_j (B \setminus i)] = \frac{1}{1-\lambda} [\Delta_i V (B \setminus i) - R_j (B \setminus i)].
\]

Notice that it only incorporates the direct surplus that is generated by hospital \( j \)'s inclusion
in the network \( B \setminus i \) and therefore excludes the appearance of terms with \( R_k (B \setminus i, j) \). We
make this simplifying assumption hesitantly because, as in all model involving bounded
rationality, there is no unambiguously correct formulation. In the end the justification for
the assumption depends mainly on how well it fits the data and only partly on the plausibility
of the modeling.

Before turning to estimation, two additional issues need mention. Within a market some
hospitals may be capacity constrained. From the viewpoint of the MCO, if hospital \( k \) is
capacity constrained when the network is \( B \), then it can not substitute for a neighboring
hospital that is trying to hold the MCO up for a better payment rate. We do not attempt to
incorporate this here. Second, as a result of the data that we have, we model the industry
as if the metropolitan area has one MCO that enrolls the entire population. There are in fact always several MCOs. This introduces a number of complications that our model does not incorporate. For instance, capacity-constrained hospitals can force competing MCOs to bid for their capacity and therefore force up their rates relative to what our model predicts. Also, quite conceivably, different MCOs may negotiate with different levels of rationality. The attenuation parameter $\rho$ may help some with this issue. Nevertheless our model’s high level of aggregation may cause estimation difficulties and should be kept in mind.

4 Estimating Equation

Solving for $R_j(B \setminus i)$ yields:

$$R_j(B \setminus i) = \frac{\kappa}{1 + \kappa} \alpha \Delta_j F(B \setminus i) + \frac{1}{1 + \kappa} C_j(B \setminus i)$$

which can be substituted into equation 1. Making this substitution and solving for $R_i(B)$ yields:

$$R_i(B) = \frac{\kappa}{1 + \kappa} \alpha \Delta_i F(B) + \frac{1}{1 + \kappa} C_i(B) - \frac{\kappa}{1 + \kappa} \rho_1 \sum_{j \neq i \in B} R_j(B)$$

$$+ \left( \frac{\kappa}{1 + \kappa} \right)^2 \rho_1 \sum_{j \in B \setminus i} \alpha \Delta_j F(B \setminus i) + \frac{\kappa}{(1 + \kappa)^2} \rho_1 \sum_{j \in B \setminus i} C_j(B \setminus i)$$

Equation 6 could, in principle, be estimated from our data. However, $\Delta_i F(B)$ is highly correlated with $\sum \Delta_j F(B \setminus i)$, which makes estimation difficult. To get around this problem, we make several transformations to the estimation equation.
First, we define the following terms:

\[ R_B = \sum_{j \in B} R_j(B) \]
\[ \Delta_B F = \sum_{j \in B} \Delta_j F(B) \]
\[ C_B = \sum_{j \in B} C_j(B) \]
\[ X_i = \sum_{j \in B \setminus i} \Delta_j F(B \setminus i) - \Delta_B F \]
\[ Y_i = \sum_{j \in B \setminus i} C_j(B \setminus i) - C_B. \]

We then substitute these terms into equation 6 and rearrange to yield:

\[ R_i = \frac{\kappa}{1 + \kappa - \kappa \rho} \left\{ \alpha \Delta_i F(B) + \frac{1}{\kappa} C + \frac{\rho \kappa}{1 + \kappa} \alpha \Delta_B F + \frac{\rho}{1 + \kappa} C_B - \rho R_B + \frac{\rho \kappa}{1 + \kappa} \alpha X_i + \frac{\rho}{1 + \kappa} Y_i \right\} \]

(7)

We are also interested in estimating a more linear version of equation 9. The equation resembles a simple reduced form regression with the following form:

\[ R_i = \beta_0 + \beta_1 WTP_i + \beta_2 C_i + \beta_3 X_i + \beta_4 Y_i \]

(8)

where
\[ \beta_0 = \frac{\kappa}{1 + \kappa - \kappa \rho} \left[ \frac{\rho \kappa}{1 + \kappa} \Delta_B F + \frac{\rho}{1 + \kappa} C_B - \rho R_B \right] \]

\[ \beta_1 = \frac{\kappa \alpha}{1 + \kappa - \kappa \rho} \]

\[ \beta_2 = \frac{\kappa}{1 + \kappa - \kappa \rho} \cdot \frac{1}{\kappa} \]

\[ \beta_3 = \frac{\kappa}{1 + \kappa - \kappa \rho} \cdot \frac{\rho \kappa}{1 + \kappa} \]

\[ \beta_4 = \frac{\kappa}{1 + \kappa - \kappa \rho} \cdot \frac{\rho}{1 + \kappa} \]

Equation 8 is highly intuitive: revenues depend on value, cost, and leverage. Moreover, the structural model gives us precise metrics for the WTP and leverage parameters. In our initial analyses, we will perform OLS regressions of equation 8 without regard for the structure underlying the individual coefficients. If bargainers act with zero foresight, then \( \beta_3 = \beta_4 = 0 \). We may consider this OLS regression to be a “semistructured” extension to CDS. After performing the OLS regressions, we will directly estimate the parameters of the structural model using nonlinear least squares.

Our nonlinear equation 7 will not be strictly comparable to the linear equation, since we do not include a constant term in the nonlinear equation. In order to make it possible to compare the \( R^2 \) of the two equations, we subtract the market-specific mean of revenues (\( R_B/N \), where \( N \) is the number of hospitals) from both sides. The resulting equation is:

\[
R_i - R_B/N = \frac{\kappa}{1 + \kappa - \kappa \rho} \left\{ \alpha \Delta_i F(B) + \frac{1}{\kappa} C + \frac{\rho \kappa}{1 + \kappa} \alpha \Delta_B F + \frac{\rho}{1 + \kappa} C_B \right. \\
- \left( \rho + \frac{1 + \kappa - \kappa \rho}{N \kappa} \right) R_B + \frac{\rho \kappa}{1 + \kappa} \alpha X_i + \frac{\rho}{1 + \kappa} Y_i \right\} \tag{9}
\]
5 Data

We use patient discharge records and hospital financial statements collected by the California Office of Statewide Health Planning and Development (OSHPD). OSHPD data have been used in numerous studies (including CDS) of hospital competition. We supplement this data with information about hospital characteristics obtained from the American Hospital Association, zip code level demographics obtained from the U.S. Census, and travel times obtained from Mapquest and ArcInfo. We focus on four markets, corresponding to the following metropolitan areas: San Diego, San Jose, Riverside, and Sacramento. We use these markets for several reasons. First, the data include the San Diego market analyzed by CDS. Second, the markets are geographically isolated from other areas, so they are likely to be self-contained. Finally, the markets have enough hospitals that bargaining could occur, but few enough that estimation of the choice model is possible.

We use 18 large hospitals from the San Diego market in our analyses. This market had no hospital systems in 1991. CDS use several additional hospitals in San Diego: Coronado, Villa View, and San Miguel. These hospitals are very small relative to the other hospitals. We use these hospital to calculate WTP and WTP leverage, but do not use them in our final models.

San Jose has 10 large hospitals, of which three were in a single system in 1991. We treat the three hospitals as a single unit for the purposes of calculating the model variables, yielding 8 total observations for this market.

Riverside and Sacramento both have 8 large hospitals. One hospital in Sacramento had missing data and two of the hospitals were part of a system, so we had 6 separate observations for the Sacramento market.

Following CDS, we examine a period of time prior to the hospital merger wave of the mid-
1990s. Due to data availability, we estimate WTP using data from calendar year 1991 and costs and revenues using data from the 1992 fiscal year, which varied across hospitals (usually but not always July 1991 to June 1992).

5.1 Measuring Key Variables

Estimation of equation 8 requires us to construct five variables from the available data:

- $R_i$: Revenue from privately insured inpatients
- $WTP_i$: Privately insured patients’ incremental willingness to pay to include hospital i in a network.
- $WTPL_i$: Willingness to pay ”leverage” - the aggregate change in privately insured patients’ willingness to pay for all other hospitals if hospital i is excluded from the network
- $Cost_i$: The incremental cost of treating privately insured patients at hospital i if that hospital is included in the network.
- $CostL_i$: Cost ”leverage” - the aggregate change in private patient costs if hospital i is excluded from the network and its patients are reallocated to other hospitals.

Measurement of each variable provided a distinct set of challenges. We describe the measurement of each variable below.

5.2 Revenue

There is no direct measure of private inpatient revenue in the OSHPD data. Instead, OSHPD reports private inpatient charges, private outpatient charges, and private “deductions from
revenue,” where “private” includes all patients not on Medicare or Medicaid and “deductions from revenue” represent the discounts from full charges that MCOs are able to negotiate, as well as any shortfalls in payments from uninsured or self-paying patients. We do not attempt to sort out revenues from patients in MCOs from revenues from uninsured or self-paying patients.

In order to infer private inpatient revenues from these data, we must allocate the deductions of revenue to inpatient and outpatient charges. We used the following allocation rule. We calculate the total percentage adjustment to charges (i.e. the total percentage subtracted from charges) implied by the deductions and assume that both inpatient and outpatient charges were adjusted by the same percentage. For example, if inpatient charges were $50 million, outpatient charges were $25 million, and total deductions from revenue were $30 million, then deductions equal 40 percent of charges. We assume that both inpatient and outpatient revenues should then equal 60 percent of charges. Thus, inpatient revenues would equal $30 million in this example.

5.3 Willingness to Pay

In order to estimate $WTP_i$ and $WTPL_i$ we must predict market shares within narrow “micro-markets” defined by patient’s demographics, disease, and location. We do this by modifying the patient choice model in CDS. The choice model in CDS includes hospital characteristics such as ownership type and staffing levels interacted with patient characteristics such as race and major disease classification (MDC). The model also includes travel times from the centroid of patient’s residence zip code to each hospital, as well as travel times interacted with patient characteristics. Following Capps et al. (2009), we replace hospital characteristics with hospital fixed effects, which we again interact with patient characteristics.\footnote{The model with hospital fixed effects yields a better fit than the model with hospital characteristics.} The patient characteristics that we include are: indicators for age greater than 65 and age younger than
indicators for male, white race, and MDC); number of other diagnoses reported on the discharge record; number of other procedures reported on the discharge record; average income in the patient’s zip code of residence; average length of stay for the patient’s diagnosis; and the percentage of rural patients with a particular diagnosis who travel outside of their county of residence for treatment (the pcttravel variable in the CDS study that proxies for quality). We modify the MDCs to more accurately reflect clinical areas. We leave most of the MDCs unchanged, but create separate codes for all cancer diagnoses, cardiac surgery, obstetrics, and transplants.

We include a large number of interactions in the choice model. This generates very flexible substitution patterns, thereby avoiding one of the criticisms of these models. We interact each of the patient characteristics with the hospital fixed effects and with the travel time between the patient’s home zip code and the hospital. We also add a set of interactions between specific patient DRGs and the existence of a hospital program to treat those DRGs. These interactions are: neurological diagnosis interacted with the presence of a neuro ICU; respiratory diagnosis interacted with pulmonary ICU; cardiovascular diagnosis interacted with cardiac catheterization services; obstetric diagnosis interacted with delivery services; imaging DRG interacted with MRI; and psychological diagnosis interacted with psychological acute services.

The choice model generates hundreds of parameters that are not, by themselves, of interest to our present analysis. We therefore omit presenting the results of the choice model; these results are available upon request.

We use the parameter estimates from the choice model to predict each privately insured patient’s willingness to pay to visit each hospital in each micromarket, and compute $WTP_i$ in accordance with equation (x). We estimate $WTPL_i$ by recomputing $WTP_j$ for all hospitals $j \neq i$ under the assumption that hospital $i$ is not in the network, then summing these values over all hospitals $j \neq i$. 

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It is useful to consider the sources of variation that separately identify $WTP_i$ and $WTPL_i$ in our models. WTP depends on the outside share—the combined market share of all other hospitals in the market—but not on any other aspect of market structure. Leverage, on the other hand, depends on the components of the outside share. For example, suppose hospitals A and B operate in separate geographical markets, and have the same market share in all submarkets. This would yield the same WTP value for both hospitals. Now suppose B’s area is dominated by 2 large hospitals, while A’s area has 5 smaller hospitals. These different market structures would lead to different leverage values.

### 5.4 Costs

The OSHPD data report direct and total inpatient costs for all patients. We are interested in the total costs of treating privately insured inpatients. We estimate total private inpatient costs by multiplying total costs by the proportion of private patient charges to total patient charges. We call this measure $Cost_i$.

In order to compute $CostL_i$ it is necessary to measure the relative efficiency of each hospital. For example, suppose we determine that hospital X has costs that are, on average, 10 percent less than costs at hospital Y. Then if hospital Y is excluded from the network and all of its patients go to hospital X, total costs would fall by 10 percent. We would therefore compute $CostL_i$ to equal $-0.10 \cdot C_Y$, where $C_Y$ is the total cost of treating patients at hospital Y.

$Cost_i$ is a naive measure of relative efficiency. Costs per discharge may vary across hospitals because of differences in efficiency or differences in casemix. We correct for the latter by dividing cost per discharge by the average Medicare caseweight.\(^5\)

---

\(^5\)Caseweights are computed by Medicare for each DRG and used to adjust hospital payments. They may be obtained from the Federal Register. We used a caseweight file from 1992 that we had been prepared for a prior research study.
We combine the data on relative efficiency with the results of the choice model to compute $Cost_{L_i}$. We begin by determining the cost per discharge for each patient who was treated at hospital $X$, which equals the average cost per discharge at their hospital multiplied by their DRG-specific caseweight. We then use the choice model to assign that patient probabilistically to all other hospitals. We then use the relative efficiency measures to compute the expected cost of that patient if hospital $X$ is excluded from the network. In this way we can compute the total expected costs of treating the patients who are no longer treated at hospital $X$.

In addition to using a modified choice model, our analysis differs from that in CDS in a number of other ways. First, and most obviously, we estimate the structural bargaining model (equation (x)). Second, the dependent variable is now revenue, rather than profit. This is necessitated by the fact that the structural equation with profit as the dependent variable includes revenue as a predictor. We lack good instruments to resolve the obvious endogeneity problem. Third, we include three additional markets. Finally, while we use all San Diego hospitals in the choice model and computation of key variables, we exclude several from the structural analysis. We described these at the beginning of section.

6 Results

In this section, we present results from reduced form and structural regressions of revenues on WTP, WTP leverage, costs, and cost leverage.

Table 1 presents summary statistics for the 34 hospitals we include in our analyses, collectively and by market. Means of the variables were generally similar across markets. WTP and WTP leverage are higher in San Jose due to the presence of a 3-hospital system. The three-hospital system had a WTP of about 28000. The means without the 3-hospital system are similar to those in the other markets. As a robustness check on our results, we ran
models in which we set an upper limit of 15000 on the WTP of the hospital system; the results were unaffected.

Table 1 also contains expenditures per case weight, which is the cost per DRG case weight. One would expect this value to be very similar across hospitals in the same market, since competing hospitals should converge somewhat in efficiency. In our markets, however, the least efficient hospital has about 1.7 times the costs of the most efficient hospital. This suggests that hospital costs may be measured with considerable error. The measurement error in costs will also affect cost leverage and may make it more difficult to identify the model parameters.

Table 2 presents results of reduced form regressions. We present results from three models:
Table 2: Reduced Form Regression Results

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>2,432.26</td>
<td>863.92</td>
<td>978.08</td>
<td>939.58</td>
</tr>
<tr>
<td></td>
<td>(2.70)*</td>
<td>(4.96)**</td>
<td>(2.80)*</td>
<td>(2.95)*</td>
</tr>
<tr>
<td>C</td>
<td>0.83</td>
<td>0.80</td>
<td>0.82</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(14.31)***</td>
<td>(9.78)***</td>
<td>(10.54)***</td>
<td></td>
</tr>
<tr>
<td>X</td>
<td>1,003.86</td>
<td>915.20</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.30)</td>
<td>(1.23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Y</td>
<td>0.47</td>
<td></td>
<td>0.47</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>_cons</td>
<td>25,196,821.66</td>
<td>-5,489,836.96</td>
<td>-6,700,561.36</td>
<td>-7,319,981.10</td>
</tr>
<tr>
<td></td>
<td>(4.79)**</td>
<td>(2.83)*</td>
<td>(4.17)**</td>
<td>(4.42)**</td>
</tr>
<tr>
<td>R²</td>
<td>0.17</td>
<td>0.86</td>
<td>0.86</td>
<td>0.87</td>
</tr>
<tr>
<td>N</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>40</td>
</tr>
</tbody>
</table>

* p < 0.1; ** p < 0.05; *** p < 0.01

WTP on its own; WTP and costs; and WTP, WTP leverage, costs, and cost leverage. Column (1) shows that WTP on its own is a strong predictor of revenue. When we add costs, the coefficient on WTP becomes smaller, but remains significant. This estimate changes very little when we add WTP leverage and cost leverage. Neither WTP leverage nor cost leverage are significant, nor are they jointly significant. However, WTP and WTP leverage are jointly significant, with \( P = 0.005 \). This suggests that WTP leverage belongs in the model.

The reduced form results suggest that leverage may be important. Additionally, the theoretical results developed in section 3 suggest that we can impose additional restrictions on the parameters. The additional restrictions may lead to more precise estimates of the leverage effect.
Table 3: Nonlinear Least Squares Estimates of Structural Bargaining Equation

<table>
<thead>
<tr>
<th></th>
<th>(1) SD only</th>
<th>(2) SD excluded</th>
<th>(3) All mkts</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\kappa)</td>
<td>0.49</td>
<td>0.51</td>
<td>0.51</td>
</tr>
<tr>
<td></td>
<td>(3.36)***</td>
<td>(4.23)***</td>
<td>(6.80)***</td>
</tr>
<tr>
<td>(\rho)</td>
<td>0.47</td>
<td>0.52</td>
<td>0.50</td>
</tr>
<tr>
<td></td>
<td>(2.42)**</td>
<td>(1.73)*</td>
<td>(3.98)**</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>3,184.92</td>
<td>1,580.95</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.99)***</td>
<td>(2.54)**</td>
<td></td>
</tr>
<tr>
<td>(\alpha) (San Diego)</td>
<td></td>
<td>3,237.06</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(6.79)***</td>
</tr>
<tr>
<td>(\alpha) (Other markets)</td>
<td></td>
<td>1,563.10</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(2.99)*</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.92</td>
<td>0.82</td>
<td>0.85</td>
</tr>
<tr>
<td>(N)</td>
<td>18</td>
<td>22</td>
<td>40</td>
</tr>
</tbody>
</table>

\(t\) statistics in parentheses.

Table 3 presents nonlinear least squares estimates of the structural model parameters. Note that the adjusted \(R^2\) drops from 0.87 in the reduced form model (4) to 0.85 in the NLS model (3); the structure contains some additional restrictions that are not in the OLS model.

We present three sets of results. Model (1) includes only the 18 hospitals in our largest market, San Diego. Model (2) includes only the 22 hospitals in the three other markets (Riverside, Sacramento, and San Jose). The parameter estimates in the first two models suggest that we may want to allow some of our parameters to differ across markets. We allow separate \(\alpha\)s in model (3). A \(\chi^2\) test confirms that the two \(\alpha\) values in model (3) are not equal. We also examined models where the other parameters were also allowed to differ, but found that we were able to restrict both \(\kappa\) and \(\rho\) to be common across markets.
In all three models, the sharing parameter $\kappa$ is significant and close to 0.5. The $\alpha$ parameter is also significant in all models. The dollar value of a util appears to be considerably higher in San Diego than in the other markets. However, there is no theoretical reason to expect $\alpha$ to be the same across all markets.

Our main interest is the foresight parameter $\rho$. The $\rho$ parameter is significant in all models, and is close to 0.5 in all cases. We can also rule out $\rho = 1$. This suggests that bargainers exhibit some foresight, but that they do not fully utilize their leverage.

As a robustness check, we used several different methods to calculate the parameter variances. Specifically, we used White’s (1980) robust variance estimator and Davidson & McKinnon’s (2004) variance estimator, which tends to estimate larger variances. In each case, our estimates remained significant.

Overall, the results are very consistent. They suggest that WTP is an important predictor of revenues and that hospitals and insurers show some foresight when bargaining over surplus.

7 Merger Simulations

An important application of the original CDS model is to simulate the effect of hospital mergers on prices. CDS examined several hypothetical mergers in San Diego as if they had taken place in 1990. We focus on three of the mergers from the CDS paper:

- Scripps Memorial–Chula Vista and Paradise Valley Hospital, two of the three hospitals in the city’s south suburbs
- Paradise Valley and Mission Bay, in the south suburbs and the north section of the city, about 14 miles apart
- UCSD and Sharp Memorial, two hospitals in the city center
We also examine several simulations that were not in the CDS paper. First, we examine the merger of Scripps Chula Vista and Fallbrook, which are more than 60 miles apart. We also examine the merger of El Camino Medical Center and San Jose Medical Center, Good Samaritan Hospital, & South Valley Hospital, a three-hospital system and a single hospital in San Jose. Finally, we examine the combination of the following three mergers:

- Scripps Memorial–Chula Vista and Paradise Valley
- Alvarado, Grossmont, Scripps Mercy, and Chula Vista Medical Center
- UCSD, Children’s and Sharp Memorial

Alvarado, Grossmont, Scripps Mercy, and Chula Vista Medical Center form a ring around Scripps Chula Vista and Paradise Valley.

One implication of the nonlinear models is that the parameter values for the San Diego market are somewhat different from the parameter values for the other markets. For the San Diego hospitals, we estimate merger effects using the NLS results from the San Diego market only. For the San Jose hospitals, we use the estimates from the other markets. In both cases, we compare the nonlinear effects to the predicted effects using the linear results with WTP only.

For the purposes of computing price changes, we assume that the mergers do not affect costs or patient flows. We also ignore changes in cost leverage in order to demonstrate more clearly how changes in WTP and WTPL affect prices. Cost leverage could, however, have a substantial impact on the post-merger price. Two efficient hospitals that merge would be able to increase their bargaining power beyond the WTP and WTPL effects.

The price increases resulting from the mergers below are the combination of three factors: the increase in WTP, the change in leverage (which can go up or down), and the change
Table 4: Effect of Scripps Chula Vista/Paradise Valley Merger on WTP and WTPL

<table>
<thead>
<tr>
<th></th>
<th>Independent</th>
<th>Merged</th>
<th>Change</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTP</td>
<td>2922.83</td>
<td>3113.31</td>
<td>190.48</td>
<td>6.5</td>
</tr>
<tr>
<td>WTPL</td>
<td>732.37</td>
<td>1036.53</td>
<td>303.79</td>
<td>41.5</td>
</tr>
</tbody>
</table>

in the revenues of other hospitals. WTP always increases following a merger. WTPL, on the other hand, can go up or down (simulation #4 provides an example of a large drop in WTPL). The last factor, changes in the revenues of other hospitals, comes into play when multiple mergers take place.

We focus on three specifications, corresponding to columns (1) and (2) of Table 2 and column (3) of Table 3. The first specification uses the change in WTP, but does not account for costs or include any measures of leverage. This specification is equivalent to that used in the CDS paper. The second specification uses the model that controls for costs, but again does not include leverage. The third specification uses the estimates from the nonlinear model for all markets combined. For the San Diego mergers, we use the $\alpha$ parameter value for San Diego. For the San Jose merger, we use the $\alpha$ parameter value for all other markets.

7.1 Simulation #1: Scripps Chula Vista and Paradise Valley Hospital

Table 4 reports combined WTP and WTPL for Scripps Chula Vista and Paradise Valley Hospital before and after a hypothetical merger. Both hospitals are located in the south suburbs, and there are few alternatives in the immediate area. The CDS analysis found the potential for a large price increase following the merger of these two hospitals.

WTP for the merging hospitals increases by about 6.5 percent while WTPL increases by 41.5 percent. The vast majority (57%) of the increase in leverage is enjoyed by two hospitals, the
Table 5: Effect of Scripps Chula Vista/Paradise Valley Merger on Revenue and Price

<table>
<thead>
<tr>
<th>Predicted revenue increase</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear, WTP only</td>
<td>463,297</td>
</tr>
<tr>
<td>Linear, WTP &amp; cost</td>
<td>164,559</td>
</tr>
<tr>
<td>Nonlinear</td>
<td>400,990</td>
</tr>
</tbody>
</table>

Community Hospital of Chula Vista, which is the third hospital serving the South Suburbs, and UCSD, which is located downtown but also draws heavily from the South Suburbs.

Table 5 presents the predicted increases in revenue for both the linear and nonlinear results. In the linear model (using WTP only), total revenue is predicted to increase by $550 thousand, yielding a percentage increase in revenue and price of 3.5 percent. The increase in revenue based on the nonlinear model is $360 thousand, or 2.3 percent. Thus, the nonlinear model predicts a much smaller increase in price than the WTP-only linear model.

7.2 Simulation #2: Paradise Valley and Mission Bay

Table 6 reports combined WTP and WTPL for Paradise Valley and Mission Bay before and after a hypothetical merger. These two hospitals are located about 14 miles apart. Paradise Valley is in the south suburbs, while Mission Bay is on the north side of the city, near UCSD Hillcrest hospital. Because of the distance, the hospitals are unlikely to generate a large increase in WTP. CDS used this hospital combination to demonstrate that their method does not automatically predict a large price increase.

In this case, WTP for the merging hospitals increases by 0.2 percent, and WTPL increases by 41.9 percent. Table 7 presents the resulting increases in price and revenue. The linear model predicts a 0.1 percent increase in price. The nonlinear model predicts a 1.9 percent
Table 6: Effect of Paradise Valley/Mission Bay Merger on WTP and WTPL

<table>
<thead>
<tr>
<th></th>
<th>Independent</th>
<th>Merged</th>
<th>Change</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTP</td>
<td>2324.8</td>
<td>2331.7</td>
<td>6.9</td>
<td>0.2</td>
</tr>
<tr>
<td>WTPL</td>
<td>565.4</td>
<td>629.3</td>
<td>973.9</td>
<td>41.9</td>
</tr>
</tbody>
</table>

Table 7: Effect of Paradise Valley/Mission Bay Merger on Revenue and Price

<table>
<thead>
<tr>
<th>Predicted revenue increase ($)</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear, WTP only</td>
<td>16,782</td>
</tr>
<tr>
<td>Linear, WTP &amp; cost</td>
<td>5,961</td>
</tr>
<tr>
<td>Nonlinear</td>
<td>170,830</td>
</tr>
</tbody>
</table>

increase in price, which is somewhat larger than expected. Most of the increase can be attributed to the change in leverage. The hospitals contributing almost all of the leverage increase are UCSD, Grossmont, and Scripps Mercy, all three of which are located between the two merging hospitals. Additionally, UCSD has a very large share of some submarkets, so small increases in that share can have potentially large effects on its WTP.

7.3 Simulation #3: Scripps Chula Vista and Fallbrook

Table 8 reports combined WTP and WTPL for Scripps Chula Vista and Fallbrook before and after a hypothetical merger. Scripps Chula Vista is in the south suburbs and Fallbrook is in the far north suburbs, so there should be very little possibility that the merger would have any effect on price, whether through WTP or leverage. We include this merger to show that our method does not automatically predict a substantial price increase.

Not surprisingly, the merger resulted in no increase in WTP. The hospitals also experienced a drop in leverage—the leverage of the surrounding hospitals increased by relatively small
Table 8: Effect of SCV/Fallbrook Merger on WTP and WTPL

<table>
<thead>
<tr>
<th></th>
<th>Independent</th>
<th>Merged</th>
<th>Change</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTP</td>
<td>2796.5</td>
<td>2796.5</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>WTPL</td>
<td>422.7</td>
<td>322.0</td>
<td>-100.7</td>
<td></td>
</tr>
</tbody>
</table>

Table 9: Effect of SCV/Fallbrook Merger on Revenue and Price

<table>
<thead>
<tr>
<th></th>
<th>Predicted revenue increase ($)</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear, WTP only</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>Linear, WTP &amp; cost</td>
<td>0 0.0</td>
<td></td>
</tr>
<tr>
<td>Nonlinear</td>
<td>-35,268</td>
<td>-0.2</td>
</tr>
</tbody>
</table>

amounts, which did not offset the lost leverage resulting from a merger. The result was a slight drop in revenues.

7.4 Simulation #4: UCSD and Sharp Memorial

Table 10 reports combined WTP and WTPL before and after a hypothetical merger for two hospitals near the center of San Diego: UCSD and Sharp Memorial. WTP for the merging hospitals increases by 8.0% following the merger, and WTPL increases by 162.3%. The largest contributor to this increase in leverage is Children’s Hospital. Children’s only competes for patients under the age of 18. However, it is a large hospital and is geographically very close to Sharp Memorial. Additionally, about 25% of the patients at Sharp Memorial were under the age of 18, so the two hospitals are in close competition for an important market segment. Children’s accounts for about 24% of the increase in leverage. The next two hospitals making the largest contribution to the increase in leverage are Grossmont and Mercy. Both hospitals are located less than 15 minutes from Sharp Memorial. Together, all three hospitals account for 57% of the increase in leverage.
Table 10: Effect of UCSD/Sharp Memorial Merger on WTP and WTPL

<table>
<thead>
<tr>
<th></th>
<th>Independent</th>
<th>Merged</th>
<th>Change</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTP</td>
<td>15939.8</td>
<td>17212.0</td>
<td>1272.2</td>
<td>8.0</td>
</tr>
<tr>
<td>WTPL</td>
<td>7289.7</td>
<td>11264.3</td>
<td>3974.6</td>
<td>54.5</td>
</tr>
</tbody>
</table>

Table 11: Effect of UCSD/Sharp Memorial Merger on Revenue and Price

<table>
<thead>
<tr>
<th>Predicted revenue increase ($)</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear, WTP only</td>
<td>3,094,321</td>
</tr>
<tr>
<td>Linear, WTP &amp; cost</td>
<td>1,099,079</td>
</tr>
<tr>
<td>Nonlinear</td>
<td>2,894,100</td>
</tr>
</tbody>
</table>

Table 11 presents the resulting increases in price and revenue. As in the SCV/Paradise Valley merger, the nonlinear model predicts a smaller price increase than the linear model with WTP only, and the linear model with WTP and cost predicts the smallest price increase.

This merger would have substantial price impacts on the surrounding hospitals as well. For example, revenues at Fallbrook Hospital would drop by 3.5%. Fallbrook increases its leverage following the merger, but the increase in (level 0) revenue at UCSD/Sharp Memorial dwarfs this increase in leverage, resulting in a drop in revenue at Fallbrook. Children’s Hospital, on the other hand, experiences an increase in leverage that is large enough to counterbalance the UCSD/Sharp Memorial revenue increase and lead to a small increase in revenue.
7.5 Simulation #5: El Camino Medical Center and San Jose Medical Center, Good Samaritan Hospital, & South Valley Hospital

We next examine the hypothetical merger of a three-hospital system (San Jose Medical Center, Good Samaritan, and South Valley) in San Jose with El Camino Hospital in San Jose. San Jose Medical Center, Good Samaritan, and South Valley were already part of a hospital system in 1991, so we are simulating a merger between only two firms.

Table 12 reports combined WTP and WTPL before and after a hypothetical merger. WTP for the merging hospitals increases by 31.0% following the merger, and WTPL decreases by 247%. This large drop in leverage is not surprising. The two firms are close substitutes, and the remainder of the hospitals in the market provide only limited competition. When these two firms merge, the combined entity gains additional leverage against the remaining hospitals in the market. However, the merging firms lose the effect of the leverage they got from competing against each other. This lost leverage more than offsets the leverage they gained against the remaining hospitals.

Table 13 reports the expected impact of the merger on revenue and price. The WTP-only model yields a predicted price increase of 23.4%. The model with WTP and cost yields a price increase of 8.3%, owing to the smaller coefficient on WTP. The nonlinear structural model predicts a price increase of 4.9%. In the structural model, the increase in WTP is counterbalanced by a decrease in leverage.

While the structural model predicts a much smaller price increase, in all three cases the expected price increase would probably be substantial enough to warrant further scrutiny from antitrust authorities.
Table 12: Effect of San Jose Merger on WTP and WTPL

<table>
<thead>
<tr>
<th>Independent</th>
<th>Merged</th>
<th>Change</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTP</td>
<td>39,498</td>
<td>51,763</td>
<td>12,264</td>
</tr>
<tr>
<td>WTPL</td>
<td>3532</td>
<td>-5188</td>
<td>-8720</td>
</tr>
</tbody>
</table>

Table 13: Effect of San Jose Merger on Revenue and Price

<table>
<thead>
<tr>
<th>Predicted revenue increase ($)</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear, WTP only</td>
<td>29,829,237</td>
</tr>
<tr>
<td>Linear, WTP &amp; cost</td>
<td>10,595,115</td>
</tr>
<tr>
<td>Nonlinear</td>
<td>6,265,600</td>
</tr>
</tbody>
</table>

7.6 Simulation #6: Scripps Chula Vista and Paradise Valley Hospital; Alvarado, Grossmont, Scripps Mercy, and Chula Vista Medical Center; UCSD, Children’s, and Sharp Memorial

As a final simulation, we examine the consequences of a general consolidation in the San Diego market. Examining several mergers at once allows us to demonstrate how one merger affects the expected price change resulting from a different merger. We begin by examining the merger of four hospitals on the south side of San Diego. We then add a second merger: Scripps Chula Vista and Paradise Valley (simulation #1, above). Finally, we add a third merger, UCSD, Children’s, and Sharp Memorial (similar to simulation #3, above).

Table 14 reports combined WTP and WTPL before and after each set of hypothetical mergers. WTP for SCV and PV increases by 6.5%, as in merger simulation #1. WTP for Alvarado, Grossmont, Scripps Mercy, and CVMC increases by 20.3%. WTP for UCSD, Children’s, and Sharp Memorial increases by 22.1%. Note that these WTP increases will be the same regardless of whether other mergers are taking place.
The WTPL results in Table 12 demonstrate some of the possible interactions that can take place with multiple mergers. The change in WTP leverage highlights an important difference between our model and the model that relies on WTP alone. When all three mergers take place, WTPL increases by 1250% for Alvarado, Scripps Mercy, and Chula Vista Medical Center compared to a 5.7% drop when they merge alone. WTPL increases by 251% for SCV/PV, which is considerably larger than the increase in WTPL of SCV and PV in simulation #1. Finally, WTPL increases by 162% for UCSD and Sharp Memorial when they merge alone, or 2047% when they merge in conjunction with the other two hospital mergers. The merger of the nearby hospitals affects the leverage of the two-hospital system. The WTP-only model only allows the merger to affect the price of the merged entity. This simulation shows that if a merger is part of a more general consolidation, it will have a different impact on price than if it is taking place on its own.

Table 15 reports the expected changes in revenue and price from each of the merger combinations. The merger of Alvarado, Grossmont, Scripps Mercy, and Chula Vista Medical Center results in a price increase of 4.0% when it occurs alone—well below a level that would result in serious concern from antitrust authorities. Similarly, the merger of UCSD, Children’s, and Sharp Memorial results in a price increase of 4.4% on its own. However, when we combine these two mergers, Alvarado, Grossmont, Scripps Mercy, and CVMC are able to achieve a price increase of 8.1% and UCSD, Children’s, and Sharp Memorial are able to achieve an increase of 6.7%. Scripps Chula Vista and Paradise Valley fare poorly following these mergers, taking a hit of about 18.2% of their combined revenues. If these two hospitals merge, they would be able to reduce their loss to 3.3% of revenues. Thus, an initial set of mergers may lead other hospitals to merge to protect their market power.

The patterns in the price changes across these sets of mergers can be explained by three effects. First, WTP increases, which will lead to a price increase in the absence of other effects. Second, WTPL increases when nearby hospitals merge. Thus, each additional merger results in a further increase in WTPL. This effect also tends to increase price. Third, the
changes in WTP at the other hospitals could lead to an increase in revenues at those hospitals. Level 1 rationality means that the bargainers consider how much revenues will increase at other hospitals if hospital \( i \) exits the network, relative to their revenues with hospital \( i \) in the network. The size of this effect could actually be smaller after other hospitals merge if the other network is able to achieve a large price increase. As in previous merger simulations, the remaining hospitals in the network may actually see a decline in revenues as a result of a merger.

### 7.7 Summary of simulations

Overall, the above simulations demonstrate several possible outcomes. The linear WTP-only model predicts that, following a merger, the merged entity’s prices will increase (though not always by a large margin) and the other hospitals’ prices will not change. The structural model predicts that the merged entity’s prices will increase, sometimes by less than the WTP model predicts and sometimes by more. In the case of close substitutes, the structural model predicts smaller price increases than the WTP-only model. The implication of our theoretical model is that hospitals may have market power prior to merging due to the leverage they possess. Consider a market with just two hospitals. The payer may realize that if it drops one hospital from its network, it will have to bargain with the second hospital as if the latter were a monopolist. This confers power to the first hospital. The same mechanism gives power to the second hospital. Thus, the two hospitals may enjoy a measure of monopoly power even without merging, and lessen the effect of the merger. In most cases, however, leverage increases following a merger, which should lead to higher prices.

Given the many steps required to estimate cost leverage, and the quality of the cost data available to us, we suspect that there may be measurement error. This may have caused attenuation bias in the estimated impact of the increase in leverage on price. Although our analyses demonstrate several important issues that could arise in merger analyses, it is
Table 14: Effect of three mergers on WTP and WTPL

<table>
<thead>
<tr>
<th>Each merger separately</th>
<th>Independent</th>
<th>Merged</th>
<th>Change</th>
<th>Percent Change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alvarado/Grossmont/Scripps Mercy/CVMC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTP</td>
<td>20,541.9</td>
<td>24,710.6</td>
<td>4168.7</td>
<td>20.3</td>
</tr>
<tr>
<td>WTPL</td>
<td>1400.4</td>
<td>1320.1</td>
<td>-80.3</td>
<td>-5.7</td>
</tr>
<tr>
<td>UCSD/Children’s/Sharp Memorial</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTP</td>
<td>32,513.0</td>
<td>39,695.0</td>
<td>7182.0</td>
<td>22.1</td>
</tr>
<tr>
<td>WTPL</td>
<td>862.5</td>
<td>6410.3</td>
<td>1781.4</td>
<td>162.3</td>
</tr>
<tr>
<td>SCV/PV</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTP</td>
<td>2922.8</td>
<td>3113.3</td>
<td>190.5</td>
<td>6.5</td>
</tr>
<tr>
<td>WTPL</td>
<td>732.4</td>
<td>1036.5</td>
<td>303.8</td>
<td>41.5</td>
</tr>
<tr>
<td>WTPL–Alvarado/Grossmont/Scripps Mercy/CVMC &amp; UCSD/Children’s/Sharp Memorial</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alvarado/Grossmont/Scripps Mercy/CVMC</td>
<td>1400.4</td>
<td>18,487.4</td>
<td>17,087.0</td>
<td>1220</td>
</tr>
<tr>
<td>UCSD/Children’s/Sharp Memorial</td>
<td>862.5</td>
<td>18,122.2</td>
<td>17,259.7</td>
<td>2001</td>
</tr>
<tr>
<td>WTPL–All 3 mergers</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alvarado/Scripps Mercy/CVMC</td>
<td>1400.4</td>
<td>18,899.0</td>
<td>17,498.6</td>
<td>1250</td>
</tr>
<tr>
<td>UCSD/Sharp Memorial</td>
<td>862.5</td>
<td>18,521.9</td>
<td>17,659.4</td>
<td>2047</td>
</tr>
<tr>
<td>SCV/PV</td>
<td>732.4</td>
<td>2572.5</td>
<td>1840.1</td>
<td>251.2</td>
</tr>
<tr>
<td>Linear, WTP only</td>
<td>Predicted revenue increase ($)</td>
<td>Percent increase</td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------</td>
<td>-------------------------------</td>
<td>-----------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alvarado/Grossmont/Scripps Mercy/CVMC</td>
<td>10,139,362</td>
<td>6.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UCSD/Children’s/Sharp Memorial</td>
<td>17,468,491</td>
<td>7.0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SCV/PV</td>
<td>590,524</td>
<td>3.8</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Linear, WTP &amp; Cost</th>
<th>Predicted revenue increase ($)</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alvarado/Grossmont/Scripps Mercy/CVMC</td>
<td>4,691,288</td>
<td>3.3</td>
</tr>
<tr>
<td>UCSD/Children’s/Sharp Memorial</td>
<td>8,082,335</td>
<td>3.3</td>
</tr>
<tr>
<td>SCV/PV</td>
<td>214,358</td>
<td>1.4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Nonlinear</th>
<th>Predicted revenue increase ($)</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Each merger separately</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alvarado/Grossmont/Scripps Mercy/CVMC</td>
<td>5,942,500</td>
<td>4.0</td>
</tr>
<tr>
<td>UCSD/Children’s/Sharp Memorial</td>
<td>10,944,000</td>
<td>4.4</td>
</tr>
<tr>
<td>SCV/PV</td>
<td>400,990</td>
<td>2.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Alvarado/Grossmont/Scripps Mercy/CVMC &amp; UCSD/Children’s/Sharp Memorial</th>
<th>Predicted revenue increase ($)</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alvarado/Grossmont/Scripps Mercy/CVMC</td>
<td>11,973,000</td>
<td>8.1</td>
</tr>
<tr>
<td>UCSD/Children’s/Sharp Memorial</td>
<td>16,575,000</td>
<td>6.7</td>
</tr>
<tr>
<td>SCV/PV (not merged)</td>
<td>-2,766,000</td>
<td>-18.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>All three systems</th>
<th>Predicted revenue increase ($)</th>
<th>Percent increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alvarado/Grossmont/Scripps Mercy/CVMC</td>
<td>9,658,000</td>
<td>6.5</td>
</tr>
<tr>
<td>UCSD/Children’s/Sharp Memorial</td>
<td>11,449,000</td>
<td>4.6</td>
</tr>
<tr>
<td>SCV/PV</td>
<td>-513,000</td>
<td>-3.3</td>
</tr>
</tbody>
</table>
possible that available cost data are not sufficient to identify merger effects with accuracy.

8 Conclusions

Economic theories of bargaining usually assume that agents display considerable foresight, anticipating how each decision affects all future decisions. Such theories often require agents to possess remarkable computational skills that would challenge any real world agent, as well as any econometrician attempting to test the theories. Models of bounded rationality, such as the theory of K-level rationality, make fewer demands on the cognitive skills of bargainers but even these models usually involve symmetric games and have rarely, if ever, been tested outside of experimental settings. It has proven challenging to document foresight among real world bargainers.

The main contribution of this paper is to develop a novel structural model that allows for one level of foresight in bargaining between a single principal (the managed care payer) and multiple asymmetric agents (the hospital). When the payer negotiates with a particular hospital, both parties understand that if the negotiation breaks down and the hospital is excluded from the network, that will affect the value of the network, because patients will have fewer options, and the cost of the network, because the excluded hospital may be more or less efficient than average. We might call this the naive impact of bargaining. But the payer and hospital may display greater foresight, recognizing that by excluding the hospital, the payer changes the negotiating dynamic with the remaining hospitals. Specifically, excluding the first hospital alters the naive impact of bargaining with the remaining hospitals. We use the terms WTP leverage and cost leverage to describe this impact.

We derive expressions for WTP leverage and cost leverage that can be computed using readily available inpatient utilization and hospital financial data. We introduce into the model an “attenuation” parameter $\rho$ that, in an ad hoc fashion, accounts for the real world
uncertainties faced by managed care payers and providers as they consider the consequences should they fail to reach agreement. The attenuation parameter ranges from 0 (no foresight) to 1 (one level of foresight.) The resulting structural model relates WTP, costs, WTP leverage, and cost leverage to hospital revenues. The model includes three parameters to be estimated from the data: the dollar value of a util, the split of the rents between payer and hospitals, and the attenuation parameter $\rho$. The model can be readily estimated using nonlinear least squares.

Examining several markets in California, we find that the nonlinear least squares model is highly predictive, explaining well over 80 percent of the variation in revenues across hospitals. Although most of the explanatory power comes from including costs on the right hand side, we can reject the null hypothesis that $\rho = 0$. We can also reject $\rho = 1$ in most specifications. Thus, we conclude that bargainers display some foresight. We use the model to predict the outcomes of several hypothetical mergers in California.

In order to make our model tractable, we have made a number of strong assumptions. First, our bargainers do not renegotiate if a payer does not contract with one hospital and then a second, it cannot try again with the first. This reflects what we have heard from payers and hospitals in informal discussions, where they express concern that if a negotiation breaks down, they may not return to it for a considerable time, during which the payer may negotiate with other hospitals. To some extent, the fact that $\rho < 1$ may reflect the fact that the payer does eventually attempt to renegotiate. Second, we do not consider the possibility that the payer would conduct an auction, for example by agreeing to contract with the lowest bidders. This reflects the realities of network formation. Finally, we do not allow for more than one level of foresight. This is largely for tractability of the theory and ease of empirical implementation. Given these limitations, as well as the data concerns described above, we are hesitant to take our predictions as the dernier cri in merger forecasts.
References


