Mergers When Prices Are Negotiated: Evidence from the Hospital Industry*

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Abstract

In many markets prices are negotiated by the parties. We study the effects of mergers on outcomes in these markets. Our focus is the health care market, where in recent years, many hospitals have merged, in part to gain bargaining leverage with managed care organizations (MCOs). We formulate a bargaining model between hospitals and MCOs, and estimate the model using discharge data and administrative claims data. We demonstrate theoretically and empirically how patient coinsurance, and hospital mergers impact the negotiated prices. We further use the results to analyze a proposed hospital merger in Northern Virginia and the effect of remedies that have been proposed.

Preliminary work in progress.

The views expressed here are the authors alone and do not necessarily reflect the views of the Federal Trade Commission or any Commissioner.

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1 Introduction

In many markets prices are negotiated by the relevant parties rather than set by one of the sides or determined by means of an auction. Examples, from a wide range of microeconomic fields, include (i) wholesale prices set between upstream and downstream firms; (ii) consumer prices of, for example, houses set between buyers and sellers, or cars negotiated between consumers and dealers; (iii) wages negotiated between firms and workers. In all these examples, each side has an incentive to improve its bargaining position. One of the ways that firms may achieve a better bargaining position is through a horizontal merger.\(^1\) Theoretically, the impact of a merger on prices in the bargaining context will be different in magnitude and potentially even sign than in a Bertrand setting.\(^2\)

In this paper we quantify the effect of mergers on payments made by health plans to hospitals. Managed care organizations (MCOs) are a significant force in restraining medical care prices (Cutler et al., 2000). MCOs obtain lower prices from providers than traditional fee-for-service insurance arrangements because they can credibly threaten to exclude providers from their networks. When facing a significant managed care presence, one important strategic response for hospitals (and other providers) is consolidation into systems. Hospital systems will have greater bargaining leverage than individual hospitals given that the threat of removing an entire system from the network is more costly to the MCO than removing just a single hospital. Indeed, over the last 25 years, as MCO enrollment has surged, hospital markets have become significantly more concentrated due to mergers (Gaynor and Town, 2012). This consolidation has resulted in the hospital industry becoming the focus of more federal

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\(^1\)For example, Deaton and Beaumont (1980) and Deaton and Beaumont (1982) find that from size impacts whether unions of different work types negotiate separately or integrate and negotiate jointly. Chipty (1995) finds that larger cable providers are able to bargain for better input prices. Similarly, Sorensen (2003) finds that larger health plans are able to secure better prices from hospitals. Interestingly, he finds that payers ability to shift market share by channeling patients to lower cost hospitals has a larger effect on prices. Finally, Ho (2009) finds that hospitals that are part of a hospital system are able to obtain higher reimbursement rates from health care providers.

\(^2\)Horn and Wolinsky (1988a,b) show that total surplus of the integrated party can be lower than the sum of the surplus of the parties bargaining separately. Chipty and Synder (1999) show that a horizontal merger will not improve the bargaining outcome for parties whose contribution to total surplus is greater than the average contribution of the merging parties.
horizontal merger litigation than any other industry over this period.\footnote{Since 1989, there have been thirteen federal hospital antitrust trials. Most recently, the Federal Trade Commission successfully challenged mergers in Toledo, OH (\textit{In the Matter of ProMedica Health System Inc. Docket No. 9346, 2011}) and Rockford, IL (\textit{In the Matter of OSF Healthcare System and Rockford Health System, Docket No. 9349, 2012}).} The hospital industry’s large share of GDP (5.3\%) implies that understanding its structure and performance has implications for aggregate economic activity.

We study how hospital mergers (and potential policy remedies) affect prices and welfare for managed care patients. To do so, we formulate and estimate a structural bargaining model between hospitals and MCOs over prices for inpatient services. We estimate the model using a unique dataset that provides MCO coinsurance amounts and transaction-level hospital prices for four MCOs for Northern Virginia. We use the estimated model to analyze the price and welfare impacts of actual and proposed hospital mergers in Northern Virginia, and restrictions on hospital bargaining conduct as imposed by the Federal Trade Commission (FTC) in a recent merger decision. While our empirical application is to hospital competition, we believe that our approach can be used more generally to understand mergers and competition in industries where prices are determined by negotiation between differentiated sellers and a small numbers of “gatekeeper” buyers who act as intermediaries for end consumers.

We model the managed care process in steps. In the first step hospital systems and MCOs providers negotiate the price hospitals will be paid from each payer for treating patients. Next, patients get health draws and decide whether to seek hospital care and if so at which hospital. In the first stage MCOs and hospital systems simultaneously bargain over base prices in a set of separate rooms, with one room for each hospital system and MCO pair. In these negotiations, MCOs act as agents of employers, seeking to maximize a weighted sum of patient welfare (as computed from the choice model described below), and the insurer costs to hospitals. This is consistent with a situation where employers have existing contracts with MCOs to administer healthcare services for their employees in exchange for a fixed management fee. Hospitals, which may be not-for-profit, seek to maximize a weighted sum of profits and quantity. The outcome we focus on is the Nash bargaining solution.

After prices are set, MCO enrollees receive illness shocks. Each enrollee requiring hospital
care chooses a hospital based on her out-of-pocket price and the interaction of her characteristics with hospital characteristics, including her distance to the hospital and the resource intensity of her illness interacted with hospital indicators. The out-of-pocket price is calculated as the negotiated base price multiplied by the coinsurance rate, which is taken as given, and adjusted for the complexity of the particular illness. This choice model allows us to compute the expected patient welfare as a function of the network of hospitals and prices, which affects the bargaining value of the MCO.

We show that equilibrium prices can be expressed by a formula that is analogous to the standard Lerner Index equation one would get, for example, from a Bertrand game, but where actual price sensitivity is replaced by an effective price sensitivity. The difference between the actual and effective price sensitivities depends on parameters of the bargaining game. When hospitals have all the bargaining power, the actual and effective price sensitivities are equal and hence prices are the same as under Bertrand competition. When the MCO has some bargaining power the two will not be equal. With equal marginal costs across hospitals and single-firm hospitals, the effective price sensitivity is higher than the actual price sensitivity; thus, markups will be lower than under Bertrand competition. More generally, the effects could go either way. Unlike standard, static oligopoly models, mergers by hospitals which do not directly compete for same patients but which treat patients from the same MCO may affect markups through multi-market contact.

To estimate the model we use state level discharge data and administrative claims data from payors. The use of administrative claims data is novel and helps in two ways. First, the claims data allow us to construct prices for each hospital-payor-year triple. A longstanding challenge in the analysis of hospital markets is the difficulty of acquiring actual transaction-level prices. Many studies instead create proxies constructing by dividing total revenues by quantity, but these data may be very imprecise. Second, these data allow us to construct patient-specific coinsurance rates.

We estimate our model in two steps. First, using the patient hospital choice we estimate a multinomial logit model. Second, we estimate Nash bargaining weights, the hospital cost function and parameters of the MCO objective by forming moment conditions based on the
interaction of instruments and the difference between observed prices and those predicted by the bargaining model. The instruments we use are demand shifters, and observable cost shifters. We use the estimates to compute markups, and then use the markups to back-out marginal costs.

We find that patients pay an average of 2 to 3% of the hospital bill out of their own pockets. Despite the low coinsurance rates, the estimates from the hospital choice model indicate that patients are sensitive to out-of-pocket prices when selecting a hospital: the average own-price elasticities for hospitals, in terms of the effect of a change in the negotiated price, are about 0.12. In the absence of any health insurance, own-price elasticities would be about 6. Mean Lerner indices range from 0.21 to 0.68. For stand-alone hospitals, a Lerner index of 0.60 is consistent with an own-price elasticity of 1.67. This implies that bargaining incentives make MCOs act more elastic than individual patients, but less elastic than would patients without insurance.

Using the estimated parameters of the model, we solve for the equilibrium of the model under the new ownership structure to calculate the impact of two hospital mergers on the negotiated, post-merger prices. We first examine the impact of Inova Health System’s proposed acquisition of Prince William Hospital. This proposed acquisition was challenged by the FTC due to anticompetitive concerns and ultimately abandoned. We find that this merger would have raised prices a quantity-weighted average of 4.3% at Inova’s six post-merger hospitals, including Prince William. With zero coinsurance, prices would be 3% to 4% higher than in the base case and rise a further 3% from the merger. We also examine Inova’s acquisition of Loudoun Hospital. This merger occurred in 2005 and was not challenged by federal or state agencies. We find that divesting Loudoun Hospital would only have lowered prices by an average of 1.1% at the five Inova hospitals.

Finally, we examine remedies proposed by the FTC in another case where newly acquired hospitals would have to bargain separately to lower bargaining leverage. If Prince William Hospital were to merge with Inova but bargain separately, this would have still resulted in a 4.0% average price increase relative to the base case. We attribute this similar increase to the fact that bargaining leverage changes in the same direction on both sides of the market.
This paper builds on three related literatures. First, a large literature uses pre-merger data to simulate the likely effects of mergers by using differentiated products models with price setting behavior.\(^4\) With a few exceptions (see Gaynor and Vogt, 2003), it has been difficult to credibly model the hospital industry within this framework. For instance, because consumers typically pay only a small part of the cost of their hospital care, patient choices are inelastic with respect to price implying either negative marginal costs or infinite prices under Bertrand competition. We find that the equilibrium incentives of an MCO will both be more elastic and also change in different ways following a hospital merger than would the incentives of its patients.

Second, an existing literature has focused on bargaining models in which hospitals negotiate with MCOs for inclusion in their network of providers. Capps et al. (2003) and Town and Vistnes (2001) estimate specifications that are consistent with an underlying bargaining model but neither paper fully specifies or estimates a structural bargaining model. We show that their specification corresponds to a special case of our model where coinsurance rates are zero and where prices across hospital are initially the same. Our work also builds upon the more recent work modeling the hospital/MCO bargaining process of Ho (2009), Lewis and Pflum (2011) and Ho (2006). Ho (2009) is of particular interest. She estimates the parameters of MCO choices of provider network. Our work, in contrast, focuses on the complementary price setting mechanism between MCOs and hospitals, taking as given the network structure.

Finally, our analysis is also closely related to recent work that estimates structural, multilateral bargaining models.\(^5\) Relative to this literature, we focus on modeling the consequences of mergers. Our econometric approach is differentiated from these papers in that our unobserved term reflects cost variation – which is closer to standard pricing models – instead of

\(^4\)See, for example, Berry and Pakes (1993); Hausman et al. (1994); Werden and Froeb (1994); Nevo (2000)).

variation in Nash bargaining weights as in Grennan (2010) and by our assumptions on the pass-through from negotiated prices to out-of-pocket prices.

The remainder of this paper is organized as follows. Section 2 presents our model. Section 3 discusses data and econometrics. In Section 4 provides our results. Section 5 provides counterfactuals. Section 6 concludes.

2 Model

This section describes our model of hospital and managed care bargaining, and patient choice of hospital. The product that is sold by MCOs is health administration services to self-insured employers. Employers acquire these services and insure their employees as part of the compensation package they offer to their employees. In the U.S., private health insurance is generally acquired through an employer and approximately 60% of employers are self-insured with larger employers significantly more likely to self-insure (Kaiser Family Foundation/Health Research and Educational Trust, 2011).

In self-insured plans, the employer pays the cost of its employees’ health care (less coinsurance, copays and deductibles) plus an administrative fee to the MCO. The central role of the MCO is to construct provider networks, negotiate prices, provide care and disease management services, and process medical care claims. We assume that employers have long-term contracts with MCOs, under which the MCO agrees to act in the incentives of the employers that it represents in its negotiation with hospitals, in exchange for fixed management fees.6

We model a two-stage game that follows the long-term employer/MCO contracts. In the first stage, hospital systems and MCOs negotiate the terms of hospitals’ inclusion in MCOs’ networks. Each hospital system and MCO pair negotiates separately and simultaneously for a base price for each hospital in the system. Following Horn and Wolinsky (1988a), the outcome of the negotiation process is the Nash bargaining solution, where the payoffs from agreement and disagreement depend on the equilibrium outcomes of the other pairs.

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6This assumption allows us to focus our attention on the interactions between hospitals and MCOs rather than modeling the contracts between employers and MCOs.
In the second stage, each patient receives a health status draw. If she needs to receive inpatient hospital care, she must pay a predetermined coinsurance fraction of the negotiated price for each in-network hospital, with the MCO picking up the remainder. The patient then selects a hospital in the MCO’s network – or an outside alternative – to maximize her utility. Utility is a function of hospital characteristics, distance to the hospital, intensity of resource use for the illness, and the out-of-pocket portion of price. MCOs, acting on behalf of the employers they represent, seek to maximize the weighted enrollee consumer surplus from hospital choice net of payments to hospitals. Hospital systems, which are mostly not-for-profit in our data, seek to maximize a weighted sum of profits plus quantity of patients served.

2.1 Patient choice model

We now exposit the second stage of the game. There is a set of hospitals \( j = 1, \ldots, J \), and a set of managed care companies \( m = 1, \ldots, M \). Each enrollee has health insurance issued by a particular MCO. Let \( i = 1, \ldots, I_m \) denote the enrollees of MCO \( m \). Each MCO \( m \) has a subset of the hospitals in its network; denote this subset \( N_m \). For each \( m \) and each \( j \in N_m \), there is a base price \( p_{mj} \), which was negotiated in the first stage. Let \( \vec{p}_m \) denote the vector of all negotiated base prices for an MCO.

At the start of the second stage, each patient receives a draw on her health status which determines if she has one of a number of health conditions that requires inpatient care. Let \( f_{mid} \) denote the probability that patient \( i \) at MCO \( m \) is stricken by illness \( d = 0, 1, \ldots, D \), where \( d = 0 \) implies no illness; and \( w_d \) denote the relative intensity of resource use for illness \( d \), with \( w_0 = 0 \). In our empirical analysis, \( w_d \) is observed. We assume that the price paid for treatment is \( p_{mj}w_d \), the base price multiplied by the disease weight. Therefore, the base price, which will be negotiated by the MCO and the hospital, can be viewed as a price per unit of \( w_d \). This is essentially how most hospitals are reimbursed by Medicare, and many MCOs incorporate this payment structure into their hospital contracts.

Each patient’s contract with her MCO specifies a coinsurance rate for each condition,
which we denote $c_{mid}$. The coinsurance rate specifies the fraction of the billed price $p_{mj}w_d$ that the patient must pay out of pocket. We treat $c_{mid}$ as predetermined in the sense that we do not endogenize its choice in response to counterfactual mergers or other policies.

For each realized illness, $d = 1, \ldots, D$, the patient seeks hospital care at the hospital which gives her the highest utility, including an outside option. The utility that patient $i$ enrolled in health plan $m$ receives from care at hospital $j \in N_m$ is given by

$$u_{mijd} = \beta x_{mijd} - \alpha c_{mid}w_d p_{mj} + e_{mij}. \tag{1}$$

In equation (1), $x_{mijd}$ is a vector of hospital and patient characteristics including travel time, hospital indicators, and interactions between hospital and patient characteristics (e.g., hospital indicators interacted with disease weight $w_d$), and $\beta$ is the associated coefficient vector. The out-of-pocket expense to the patient is $c_{mid}w_d p_{mj}$. As we describe below, we observe data that allow us to impute the base price, the disease weight, and coinsurance rate; hence we treat out-of-pocket price as observable.\(^7\) We let $\alpha$ denote the price sensitivity. Finally, $e_{mij}$ is an i.i.d. error term that is distributed type I extreme value.

The outside choice, denoted as choice 0, is treatment at a hospital located outside the market. The utility from this option is given by

$$u_{mi0d} = -\alpha c_{mid}w_d p_{0m} + e_{mi0}. \tag{2}$$

We normalize the quality from the outside option — i.e., the measures $x_{mi0d}$ — to 0 but we allow for a non-zero base price $p_{0m}$. Specifically, we let $p_{0m}$ be the unweighted mean of the base price vector $p_m$.\(^8\) Finally, we will assume that $e_{mi0}$ is also distributed type 1 extreme value.

There are two features of our setting that differ from standard choice models. First,\(^7\) Gaynor and Vogt (2003) also model patient utility as including price but they do not observe coinsurance rate information.

\(^8\)Note, that in the empirical analysis we include hospital fixed effects, the choice of attributes of the outside option will only scale coefficient estimates. However, because our bargaining model specifies payments from MCOs, the price of the outside option has real implications as to the bargaining model parameter estimates and counterfactual equilibrium behavior.
when choosing where to get treatment, consumers do not pay the full cost of their treatment and thus, the price coefficient reflects the disutility from the out-of-pocket cost. Second, consumers are ex-ante uncertain about the illness that they will face and their expected utility needs to integrate out over illness shocks.

Consumers’ expected utility will play an important role in the bargaining game. To compute it define $\delta_{mijd} = \beta x_{mijd} - \alpha c_{mid} w_d p_{mj}$, $j \in \{0, N_m\}$. Given the extreme value distribution, the choice probability for patient $i$ with disease $d$ as a function of prices and network structure is:

$$s_{mijd}(N_m, \vec{p}_m) = \frac{e^{\delta_{mijd}}}{\sum_{k \in 0, N_m} e^{\delta_{mkid}}}.$$  (3)

The ex-ante consumer surplus, or dollar value of expected utility, as a function of prices and the network of hospitals in the plan, is given by:

$$W_m(N_m, \vec{p}_m) = \frac{1}{\alpha} \sum_{i=1}^{I_m} \sum_{d=1}^{D} f_{mid} \ln \left( \sum_{j \in 0, N_m} e^{\delta_{mijd}} \right).$$  (4)

Another important quantity for the bargaining game is the intensity-weighted expected number of plan $m$ patients who are admitted to hospital $j$, $j \in N_m$, given by

$$q_{mj}(N_m, \vec{p}_m) = \sum_{i=1}^{I_m} \sum_{d=1}^{D} f_{mid} w_d s_{mijd}(N_m, \vec{p}_m).$$  (5)

Since prices are per unit of $w_d$, the intensity-weighted expected number of patients times price will give the expected revenue to the hospitals from plan $m$.

### 2.2 Bargaining model

We now exposit the bargaining model, which we model as a game of complete information. Assume that the $J$ hospitals are divided into $S \leq J$ systems, which together partition the hospitals. Let $J_s, s = 1, \ldots, S$, denote the set of hospitals in system $s$. Then, the bargaining occurs as follows. There are $S \times M$ negotiation rooms, each corresponding to one MCO and

\footnote{We exclude Euler’s constant from this expression.}
one hospital system. Each room simultaneously decides on the negotiated base prices for its MCO and hospital system pair. Each hospital within a system has a separate price. Thus, if a hospital system has \( J_s \) hospitals, then the corresponding system would decide on a vector of \(#(J_s)\) prices, where \(#(X)\) is the cardinality of set \(X\). We consider Nash equilibria where each MCO either contracts with all hospitals in a system or none.

Following Horn and Wolinsky (1988a), each bargaining room solves the price vector (or price scalar in the case of a stand-alone hospital) as the outcome of the Nash bargaining solution. The disagreement point for any negotiation is the value to each party of no agreement, holding the other negotiations fixed. This is often referred to as passive beliefs (McAfee and Schwartz, 1994). This is obviously a strong assumption and is made for tractability.\(^{10}\)

Starting with MCOs, we now detail the payoff structures and then use them to exposit the Nash bargaining solution for each negotiation room. Recall that each MCO, acting on behalf of its contracted employers, seeks to maximize a weighted sum of the consumer surplus of its enrollees net of the payments to hospitals. Define the ex-ante expected cost to the MCO of a given hospital network and vector of negotiated prices to be

\[
TC_m(N_m, \vec{p}_m) = \sum_{i=1}^{l_m} \sum_{d=1}^{D} (1 - c_{mid}) \sum_{j \in 0, N_m} p_{mj} f_{mid} w_{dj} s_{mijd}(N_m, \vec{p}_m). \tag{6}
\]

Then, the value for the MCO and the employer it represents is:

\[
V_m(N_m, \vec{p}_m) = \tau W_m(N_m, \vec{p}_m) - TC_m(N_m, \vec{p}_m), \tag{7}
\]

where \(\tau\) is the relative weight on employee welfare. Assume that \(N_m, m = 1, \ldots, M,\) are the equilibrium sets of network hospitals. For any system \(s\) for which \(J_s \subset N_m\), the net equilibrium value that MCO \(m\) receives from including system \(s\) in its network is \(V_m(N_m, \vec{p}_m) - V_m(N_m \setminus J_s, \vec{p}_m)\). Capps et al. (2003) refer to part of this term, \(W_m(N_m, \vec{p}_m) - W_m(N_m \setminus J_s, \vec{p}_m)\), as the “willingness-to-pay” (WTP).

Continuing to hospitals, hospital systems can be either for-profit or not-for-profit (NFP).\(^{11}\)
NFP systems may care about some linear combination of profits and weighted quantity of patients served. Let \( mc_{mj} \) denote the “perceived” marginal cost of hospital \( j \) for treating a patient from MCO \( m \) with disease weight \( w_d = 1 \). Our model of perceived marginal costs implicitly allows for different NFP objective functions: a NFP system which cares about the weighted quantity of patients it serves will equivalently have a perceived marginal cost equal to its true marginal cost net of this utility amount.

We make three additional assumptions regarding the cost structure. First, we assume that marginal costs are constant across patients and proportional to the disease weight. Second, we allow hospitals to have different marginal costs from treating patients at different MCOs, because the MCO’s approach to care management, the level of paperwork and ease and promptness of reimbursement may differ across MCOs. Finally, we specify that

\[
mc_{mj} = \gamma v_{mj} + \varepsilon_{mj},
\]

where \( mc_{mj} \) is the marginal cost for an illness with disease weight \( w_d = 1 \), \( v_{mj} \) are a set of cost shifters in the data, \( \gamma \) are parameters to estimate, and \( \varepsilon \) is the component of cost that is not observable to the econometrician. The returns that hospital system \( s \) expects to earn from a given set of managed care contracts are then:

\[
\pi_s(M_s, \{\bar{p}_m\}_{m \in M_s}, \{N_m\}_{m \in M_s}) = \sum_{m \in M_s} \sum_{j \in J_s} q_{mj}(N_m, \bar{p}_m)(p_{mj} - mc_{mj})
\]

where \( M_s \) is the set of MCOs that include system \( s \) in their network. From (9), the net equilibrium value that system \( s \) receives from including MCO \( m \) in its network is \( \sum_{j \in J_s} q_{mj}(N_m, \bar{p}_m)(p_{mj} - mc_{mj}) \).

Having specified objective functions, we now define the Nash bargaining problem. The Nash bargaining product for each pair, of hospital system \( s \) and MCO \( m \), is a function of the difference between the payoff in agreement and that in disagreement, both of which depend on the prices negotiated by other pairs. The disagreement value for the hospital system is zero, and for the MCO its the value of a network that does not include hospital system \( s \),
holding constant other prices. Formally, for system $s$ and MCO $m$, define the (asymmetric) Nash bargaining product as:

$$NB^{m,s}(p_{mj} \in J_s | p_{m,s}^{-}) = \left( \sum_{j \in J_s} q_{mj}(N_m, p_m^{-})[p_{mj} - mc_{mj}] \right)^{b_{s(m)}} \left( V_m(N_m, p_m^{-}) - V_m(N_m \setminus J_s, p_m^{-}) \right)^{b_{m(s)}},$$

(10)

where $b_{s(m)}$ is the bargaining weight of system $s$ when facing MCO $m$, $b_{m(s)}$ is the bargaining weight of MCO $m$ when facing system $s$, and $p_{m,s}^{-}$ is the vector of prices for MCO $m$ and hospitals in systems other than $s$.\footnote{Note that our assumption of constant marginal costs implies that we can consider separate bargaining problems for each MCO.} We set $b_{s(m)} + b_{m(s)} = 1$. The Nash bargaining outcome is the vector of prices $p_{mj} \in J_s$ that maximizes (10).

Let $p_m^*$ denote the Nash equilibrium vector of prices for MCO $m$. In our case, the Nash equilibrium price vector must satisfy the Nash bargain in each room, conditioning on the outcomes in each other room. Thus, $p_m^*$ will satisfy:

$$p_{mj}^* = \max_{p_{mj}} NB^{m,s}(p_{mj}, p_{m,\neq j}^* | p_{m,s}^*),$$

(11)

where $p_{m,j}^*$ is the equilibrium price vector for other hospitals in the same system as $j$.

To understand more about the equilibrium properties of our model, we solve the FOC

$$\frac{\partial \log NB^{m,s}}{\partial p_{mj}} = 0.$$  

For ease of notation, we omit the $^*$ from now on, even though all prices are evaluated at the optimum, and obtain:

$$b_{s(m)} \frac{q_{mj} + \sum_{k \in J_s} \frac{\partial q_{mk}}{\partial p_{mk}}[p_{mk} - mc_{mk}]}{\sum_{k \in J_s} q_{mk}[p_{mk} - mc_{mk}]} = -b_{m(s)} \frac{\frac{\partial V_m}{\partial p_{mj}}}{V_m(N_m, p_m) - V_m(N_m \setminus J_s, p_m)^B},$$

(12)

From (12), we can first consider the case where hospitals have all the bargaining power. If $b_{m(s)} = 0, \forall s$, then the bargaining equilibrium has the same FOCs as the Bertrand equilibrium.
with hospitals setting prices.\footnote{Just to be clear, the setting we have in mind is one in which hospitals set a different price for each MCO and this price is passed on to the MCO enrollees}

We can further rearrange the joint system of $\#(J_s)$ first order conditions from (12) to write

$$\vec{q} + \Omega(\vec{\bar{p}} - \vec{m}c) = -\Lambda(\vec{\bar{p}} - \vec{m}c)$$

where $\Omega$ and $\Lambda$ are both $\#(J_s) \times \#(J_s)$ size matrices, with elements $\Omega(j, k) = \frac{\partial q}{\partial p_{mj}}$ and $\Lambda(j, k) = b_{m(s)} A B q_{mk}$. Solving for the equilibrium prices yields

$$\vec{p} = \vec{m}c - (\Omega + \Lambda)^{-1}\vec{q},$$

where $\vec{p}$, $\vec{m}c$ and $\vec{q}$ denote the price, marginal cost and adjusted quantity vectors respectively for hospital system $s$ and MCO $m$. Equation (14) characterizes the equilibrium prices and has a form quite similar to standard pricing games. Indeed, if $b_{m(s)} = 0, \forall s$ then $\Lambda = 0$, and the FOCs are the same as in a Bertrand pricing game.

Importantly, (14) shows that, as with Bertrand competition models, we can back out implied marginal costs for the bargaining model as a linear function of prices, quantities and derivatives, given MCO and patient incentives. Using this insight, (8) and (14) together form the basis of our estimation.

### 2.3 The effect of coinsurance rates

To understand the theoretical implications of our model further, we now explore the effect of coinsurance rates on prices. As we show in On-line Appendix A, the $A$ term from equation (12) is

$$\frac{\partial V_m}{\partial p_{mj}} = -\frac{1}{\tau} \sum_{i=1}^{I_m} \sum_{d=1}^{D} c_{mid} w_{id} f_{mid s_{mijd}} - \sum_{i=1}^{I_m} \sum_{d=1}^{D} (1 - c_{mid}) w_{id} f_{mid s_{mijd}}$$

$$- \alpha \sum_{i=1}^{I_m} \sum_{d=1}^{D} (1 - c_{mid}) c_{mid} w_{id}^2 f_{mid s_{mijd}} \left( \sum_{k \in N_m} p_{mk s_{mikd}} - p_{mj} \right).$$

(15)
In the case where \( \tau = 1 \) and MCOs value patients welfare equally to dollar costs, this simplifies to

\[
\frac{\partial V_m}{\partial p_{mj}} = -q_{mj} - \alpha \sum_{i=1}^{I_m} \sum_{d=1}^{D} (1 - c_{mid}) c_{mid}^2 \sum_{k \in N_m} p_{mk} s_{mikd} - p_{mj}.
\] (16)

The first term on the right of (16) is the effect of the price rise holding consumer choices constant. This term captures the standard effect: higher prices reduce patients’ expected utility and therefore decrease the MCO’s objective function. The second term accounts for the effect due to the change in consumer choices on payments from MCOs to hospitals. As the price of hospital \( j \) rises, consumers will switch to cheaper hospitals. This term can be either positive or negative, depending on whether hospital \( j \) is cheaper or more expensive than the share-weighted price of other hospitals; the difference is reflected in the expression in the large parentheses.

Prices are the only mechanism that the MCO can use to steer patients to cheaper hospitals. Consider a hospital system with two hospitals, one low-cost and one high-cost and the case of positive coinsurance rates. The MCO and hospital system pair may not mind negotiating a high price on the high-cost hospital, as this will steer patients to the low-cost hospital, thereby increasing the joint surplus. Correspondingly, the pair would want to negotiate a relatively low price for the low-cost hospital to help steer patients to it. As coinsurance rates near one this effect disappears and low-cost hospitals will gain bargaining leverage relative to high-cost hospitals.

Now consider the case when the coinsurance rates are uniformly zero. In this case, the negotiated prices only act as a transfer between MCOs and hospitals, as prices cannot be used to steer patients. Thus, the equilibrium prices of individual hospitals within a system are not defined, and only system revenue is defined. The FOCs in (12) can then be expressed as a function of system revenue, as:

\[
\sum_{k \in J_s} q_{mk} [p_{mk} - m c_{mk}] = \frac{b_{s(m)}}{b_{m(s)}} [V_m(N_m, \overline{p_m}) - V_m(N_m \setminus J_s, \overline{p_m})].
\] (17)
From (17), with zero coinsurance, prices will adjust so that system revenues are proportional to the value that the system brings to the MCO. This result is similar to the Capps et al. (2003) model, except that Capps et al. argue that revenue should be proportional to the difference in $W_m$ rather than in $V_m$. Since Capps et al. do not account for the fact that high willingness-to-pay hospitals which are high cost are less valuable than high willingness-to-pay hospitals which are low cost, their model will provide a good approximation of counterfactuals to the extent that coinsurance rates are low and costs are similar across hospitals.

Finally, note from (17) that the prices of other systems enter into the right side of the FOC for system $s$ through $V_m$. We show in On-line Appendix C that other systems’ prices enter (17) linearly and hence that there is a closed-form solution to the vector of equilibrium prices for any market structure.

### 2.4 The effect of mergers

We now consider the impact of mergers on prices. Similarly to Bertrand competition, negotiated prices also result in an upward pricing pressure from mergers. For example, as two separate hospitals merge, by raising the price of one of the hospitals some consumers are diverted to the other hospital. Pre-merger these were considered lost profits, post-merger these are captured. This creates an incentive to raise prices relative to the pre-merger prices. A counterbalancing effect, also present in the Bertrand model is of cost efficiency. We do not model it in this paper, but in principle hospitals could merge to improve their bargaining power with supplier, thus, reducing their input costs.

However, there are two important effects that are present in our model and not in mergers with Bertrand pricing. First, a merger could improve the bargaining ability of one, or even both, of the merging hospitals. In the model this is captured by changing the bargaining parameter, $b$. For example, the parameter can be the higher of the merging parties, or in principle even higher. Since the model never speaks on exactly where the bargaining parameter comes from its a bit unclear how to change it.

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13See also Lewis and Pfum (2011) for a similar argument.
The second effect has to with a change in the leverage of the merging parties. Basically, how the threat of leaving the network will change the MCOs profits. To see this, consider further (14). The effect of bargaining on the equilibrium prices is best understood by defining the effective price sensitivity as $\Omega + \Lambda$. The FOCs from our model are identical to the Bertrand FOCs but with $\Omega + \Lambda$ instead of $\Omega$. Thus, we focus on how $\Lambda$ impacts margins.

To provide further intuition on $\Lambda$, it is useful to first consider the special case where all hospitals are single-hospital systems. In this case,

$$p_{mj} - m_{mj} = -q_{mj}\left(\frac{\partial q_{mj}}{\partial p_{mj}} + q_{mj}\frac{b_{m(j)} A}{b_{j(m)} B}\right)^{-1},$$

and $\Lambda$ is a diagonal matrix with $\Lambda_{jj} = q_{mj}\frac{b_{m(j)} A}{b_{j(m)} B}$. The $B$ term must be positive or the MCO would not gain surplus from including hospital $j$ in its network. From (15), the first term in $A$ is the negative of quantity, which is negative. If the rest of $A$ were 0, then $\Lambda_{jj}$ would be negative. In this case, MCO bargaining would add to the effective price sensitivity.

Thus, in the special case of a market with all single-hospital systems, the same bargaining equilibrium prices across hospitals, and the same and positive $b_{m(j)}$ values, price-cost margins will be lower in the bargaining equilibrium than in Bertrand competition. While these specific conditions almost surely to never hold empirically, we nevertheless believe that these forces hold broadly, that MCO bargaining lowers prices relative to fee-for-service insurance with the same coinsurance rates. With multi-hospital systems, the incentives are even more complicated but we still expect that they will push in the direction of lowering prices relative to Bertrand competition. However, there may be cases where MCO bargaining may not uniformly lower prices, notably if cost differences across hospitals are large and MCOs need to use prices to steer patients to low cost hospitals.

Considering again mergers, $B$ increases with a merger as $B$ is the joint value of the system. The $B$ term enters into the effective own-price elasticity. With Bertrand competition, a merger only changes the cross price effects, but with bargaining the effective own-price elasticity changes from a merger as well. We would expect the merger to generally make the own demand less price sensitive, providing an additional upward push to prices relative
to Bertrand competition. This effect suggests that the effect of a merger on prices will be higher with bargained prices than Bertrand competition. However, a merger also impacts the effective cross-price terms. Relative to Bertrand pricing the change in the cross price effects will be smaller if the additional terms are negative. Since these effects can be of opposite sign, the net effect of the merger relative to the Bertrand prediction is ambiguous.

Another point to note is that in Bertrand competition, a merger between two hospitals in distinct markets without any patient overlap will not affect price sensitivities and hence will have no effect on prices. Yet, if these two distinct markets are served by the same MCO, then this merger will change the effective price sensitivity and hence have an impact on price. To see this, note that the $\Omega$ matrix will be diagonal in this case (reflecting no patient overlap), but the $\Lambda$ matrix will not be. The economic reason for this is that the newly merged system would want to bargain differently from the separate hospitals. The new system will optimally redistribute where it earns its rents from the MCO across markets. The underlying logic is similar to the rationale for bundling. As an example, if the new system had a low-cost hospital in one market and a high-cost hospital in another market with otherwise similar environments, it might want to lower price on the low-cost hospital and raise price on the high-cost one. We further take from this the heuristic that mergers in relatively separate markets (e.g., two hospitals in the same metropolitan area with a substantial distance between them) may have a more important impact than one might predict with Bertrand competition.

Finally, we note that we can adapt our model to consider conduct remedies such as imposed by the Federal Trade Commission in the Evanston Northwestern Hospital (ENH) - Highland Park Hospital case. The Commission modified the Administrative Law Judge’s remedy, which was divesture, to requiring separate, fire-walled negotiations for the two merging organizations. For this remedy, ENH would have a separate bargaining room for each MCO and hence the disagreement value for the MCO would be to not have Highland Park Hospital (but still have the rest of the ENH). An analogous situation would hold for Highland Park Hospital. Even though the bargaining rooms are separate, the Highland Park bargainer

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would internalize the incentives of the system, namely that if a high price discouraged pa-
tients from seeking care at Highland Park some of them would divert instead to other ENH
members which is beneficial for the parent organization. On-line Appendix B details the
FOCs for this case.

3 Institutional setting, data and estimation

3.1 Inova/Prince William merger

We will use the model and data described above to study the competitive interactions be-
tween hospitals and MCOs in Northern Virginia. In late 2006, the Inova Health System, a
health care system based in northern Virginia, sought to acquire the Prince William Health
System, a not-for-profit institution which operated a single general acute care hospital, Prince
William Hospital (PWH), with 180 licensed beds located in Manassas, Virginia. Inova is a
not-for-profit system that operated five general acute care hospitals in northern Virginia
with a combined 1,633 beds. The Federal Trade Commission, with the Virginia Office of
the Attorney General as co-plaintiff, challenged the acquisition in May, 2008, issuing com-
plaints in federal district and administrative courts. Subsequently, the parties abandoned
the transaction.

The FTC alleged that the relevant geographic market consisted of all hospitals in Health
Planning District 8 (HPD8) and Fauquier County. This geographic area includes all five
Inova hospitals and PWH, as well as HCA Reston (located in Reston, VA), Fauquier (located
in Warrenton, VA), Potomac (located in Woodbridge, VA), and the Virginia Hospital Center
(located in Arlington, VA). The product market alleged by the FTC was general acute care,

\footnote{The hospitals in the Inova system include Fairfax Hospital, a large tertiary facility with 884 licensed
beds located in Falls Church, Virginia; Fair Oaks Hospital (182 licensed beds) located in Fairfax, Virginia;
Alexandria (334) and Mount Vernon (237) Hospital located in Alexandria, Virginia; and Loudoun Hospital
(255) located in Leesburg, Virginia.}

\footnote{PWH was later acquired by the Novant Health, a multi-hospital system based in North Carolina.}

\footnote{HPD8 is defined by the Commonwealth of Virginia as the counties of Arlington, Fairfax, Loudoun and
Prince William, and the cities of Alexandria, Fairfax, Falls Church, Manassas and Manassas Park; the towns
of Dumfries, Herndon, Leesburg, Purcellville and Vienna.}

\footnote{More distant competitors include several hospitals in the District of Columbia and the suburban areas}
inpatient services sold to managed care organizations.

Figure 1 presents a map of the locations of the hospitals in Northern Virginia. The heavy line defines the boundary of HPD8 and Fauquier County, which is the adjacent county to the south of HPD8. The two closest hospitals to PWH are members of the Inova system – Fair Oaks and Fairfax hospitals are 21 and 29 minutes drive time from PWH.

Figure 1: Hospitals in Northern Virginia

3.2 Data

Our primary data come from two sources: administrative claims data provided by four large managed care payors serving Northern Virginia (payor data) and inpatient discharge data of the District in Maryland and other hospitals in northern and central Virginia including Warren Memorial Hospital located in Warren, VA; and the University of Virginia Hospital located in Charlottesville, VA.
from Virginia Health Information. Both datasets span the years 2003 through 2006. These data are supplemented with information on hospital characteristics provided by the American Hospital Association Guide.

A longstanding challenge in the analysis of hospital markets is the difficulty of acquiring actual transaction-level prices for each hospital-payor pair in the market. The administrative claims data are at the transactions level and contain most of the information that the MCO uses to process the appropriate payment to a hospital. In particular, the claims data contain demographic characteristics, diagnosis, procedure performed, diagnosis related group (DRG), and the actual amount paid to the hospital for each claim. There are often multiple claims per inpatient stay and thus the data must be aggregated to the inpatient episode level. We group claims together into a single admission based on the date-of-service, member ID and hospital identifier. The claims often have missing DRG information. To address this issue, we use DRG grouper software from 3M to assign the appropriate DRG code to each admission.

Using the claims data, we construct risk-adjusted prices for each hospital-payor-year triple. We do this by first performing regressions of total price divided by DRG weight on gender, age and hospital dummies, separately for each payor and year. We then create the base price as the fitted regression value using all observations in the sample.

An alternative method of constructing prices would be to directly use the contracts between hospitals and MCOs. However, the complexity of these contracts resulted in difficulties in constructing apples-to-apples prices across the MCO and hospitals. As an example, we examined one hospital in our data, which had contracts of four separate types: (1) fixed-rate contracts that specified a fixed payment for each DRG; (2) per-diem contracts with fixed daily rates for medical, surgical and intensive care patients; (3) contracts with a set discount off of charges; and (4) a hybrid of the above, with switching between reimbursement regimes often based on the total charges. To avoid having to deal with a myriad of different and non-comparable contracts, we use the claims data to formulate the price measures as described above.

The claims data also contain information on the amount of the bill the patient paid out-of-pocket. This information allows us to construct patient-specific out-of-pocket coinsur-
Different insurers report coinsurance rates differently on the claims. In order to provide a standardized coinsurance measure across patients and MCOs, we formulate an expected coinsurance rate. We do this by first formulating a coinsurance amount which is the out-of-pocket expenditure net of deductibles and co-payments divided by the allowed amount. The resulting coinsurance variable is censored at zero. Then, separately for each MCO, we estimate a tobit model of coinsurance where the explanatory variables are age, female indicator, age×female, DRG weight, age×DRG weight and female×DRG weight. We then create the expected coinsurance rate for each patient as the predicted values from this regression.

The Virginia discharge data contain much of the same information as the claims data but, in general, the demographic, patient ZIP code and diagnoses fields are more accurate, and an observation in these data is at the (appropriate) inpatient admission level. The discharge data also contain more demographic information (e.g., race), and the identity of the insurer, and are a complete census of all discharges at the hospital.

For these reasons, we use the discharge data to estimate the patient choice model. We limit our sample to commercially-insured general acute care, non-newborn inpatients residing in Northern Virginia (defined as Virginia HPD 8 plus Fauquier County). Patients transferred to another general acute care hospital are excluded to avoid double counting. We exclude patients over 64 years of age to avoid Medicare Advantage and supplemental insurance patients and we drop newborn discharges treating the mother and newborn as a single choice observation. We defined the choice of an outside hospital to include patients residing within the geographic area who sought care at a hospital outside this area.

Hospital characteristics are taken from the AHA Guide of the relevant year and include: staffed beds, residents and interns per bed, indicators for ownership type (e.g., for-profit/not-profit/public), teaching hospitals, and the presence of a cardiac catheterization lab, MRI, and neonatal intensive care unit. We compute the driving time from the patient’s zip code

\[\text{Driving time} = \frac{\text{Distance}}{\text{Speed}}\]

\[\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}\]

\[\text{Speed} = \text{Average speed of travel} = \text{Average speed of travel in feet per second} \times \text{Number of seconds to travel distance} = \text{Average speed of travel in feet per second} \times \frac{\text{Distance}}{\text{Average speed of travel in feet per second}} = \text{Distance} \times \frac{\text{Average speed of travel in feet per second}}{\text{Average speed of travel in feet per second}} = \text{Distance} \times \frac{1}{\text{Average speed of travel in feet per second}}\]

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\[\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}\]

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\[\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}\]

\[\text{Speed} = \text{Average speed of travel} = \text{Average speed of travel in feet per second} \times \text{Number of seconds to travel distance} = \text{Average speed of travel in feet per second} \times \frac{\text{Distance}}{\text{Average speed of travel in feet per second}} = \text{Distance} \times \frac{1}{\text{Average speed of travel in feet per second}}\]

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\[\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}\]

\[\text{Speed} = \text{Average speed of travel} = \text{Average speed of travel in feet per second} \times \text{Number of seconds to travel distance} = \text{Average speed of travel in feet per second} \times \frac{\text{Distance}}{\text{Average speed of travel in feet per second}} = \text{Distance} \times \frac{1}{\text{Average speed of travel in feet per second}}\]

\[\text{Average speed of travel} = \frac{\text{Distance}}{\text{Time}}\]

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\[\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}\]

\[\text{Speed} = \text{Average speed of travel} = \text{Average speed of travel in feet per second} \times \text{Number of seconds to travel distance} = \text{Average speed of travel in feet per second} \times \frac{\text{Distance}}{\text{Average speed of travel in feet per second}} = \text{Distance} \times \frac{1}{\text{Average speed of travel in feet per second}}\]

\[\text{Average speed of travel} = \frac{\text{Distance}}{\text{Time}}\]

\[\text{Time} = \frac{\text{Distance}}{\text{Average speed of travel}}\]

\[\text{Average speed of travel} = \frac{\text{Distance}}{\text{Time}} = \frac{\text{Distance}}{\frac{\text{Distance}}{\text{Average speed of travel}}} = \text{Average speed of travel} \times \frac{\text{Distance}}{\text{Distance}} = \text{Average speed of travel}\]

\[\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}\]

\[\text{Speed} = \text{Average speed of travel} = \text{Average speed of travel in feet per second} \times \text{Number of seconds to travel distance} = \text{Average speed of travel in feet per second} \times \frac{\text{Distance}}{\text{Average speed of travel in feet per second}} = \text{Distance} \times \frac{1}{\text{Average speed of travel in feet per second}}\]

\[\text{Average speed of travel} = \frac{\text{Distance}}{\text{Time}}\]

\[\text{Time} = \frac{\text{Distance}}{\text{Average speed of travel}}\]

\[\text{Average speed of travel} = \frac{\text{Distance}}{\text{Time}} = \frac{\text{Distance}}{\frac{\text{Distance}}{\text{Average speed of travel}}} = \text{Average speed of travel} \times \frac{\text{Distance}}{\text{Distance}} = \text{Average speed of travel}\]
centroid to the hospital using information from MapQuest. We use DRG weights published and revised by CMS each year, which are a measure of the mean resource acuity of the diagnosis and are the primary basis for Medicare inpatient payments to hospitals.

3.3 Estimation

We estimate the model in two steps. In the first step we estimate the patient-level hospital choice model using the state discharge data augmented with price and coinsurance information from the payor data. The coefficients on characteristics, $\beta$ and the price coefficient $\alpha$ are estimated by maximum likelihood. The model includes hospital-year fixed effects and interactions of hospital fixed effects with patient disease weight. Thus, our model will identify $\alpha$ from the variation within a year across payors. The identification of the $\beta$ parameters in this model is relatively standard, e.g., travel time coefficients will be identified by the relative drop in choice probability for a hospital as travel time increases.

The remaining parameters, namely the bargaining weights $b$, the cost shifters $\gamma$, and $\tau$, the weight put on the WTP measure, are estimated by imposing the bargaining model. For any pair $(m, s)$, only the relative bargaining weights matter. Hence we impose the standard assumption that $b_m(s) + b_s(m) = 1, \forall m, s$ and only estimate bargaining weights on the MCO side.

Our estimation of the bargaining model conditions on the set of in-network hospitals and treats the negotiated prices as the endogenous variable. Combining equations (14) and (8) we define the econometric error as

$$\vec{\varepsilon}(b, \gamma, \tau) = \vec{p} - \gamma \vec{w} + (\Omega + \Lambda(b, \tau))^{-1} \vec{q}, \tag{19}$$

where (19) now makes explicit the points at which the structural parameters enter. We estimate the remaining parameters with a GMM estimator based on the moment condition that $E[\varepsilon_{mj}(b, \gamma, \tau)|Z_{mj}] = 0$, where $Z_{mj}$ is a vector of (assumed) exogenous variables.

Our estimation depends on exogenous variables $Z_{mj}$. We include all the cost shifters $v_{mj}$ in $Z_{mj}$. In specifications that include variation in bargaining weights, we include indicators
for the entities covered by each bargaining parameter. Finally, we include four other exogenous variables: predicted willingness-to-pay for the hospital, system, willingness-to-pay per enrollee, and predicted total hospital quantity, where these values are predicted using the overall mean price. From our model, price is endogenous in the first-stage bargaining model because it is chosen as part of a bargaining process where the marginal cost shock $\varepsilon$ is observed. By construction, these four exogenous variables will not be correlated with $\varepsilon$ but will correlate with price, implying that they will be helpful in identifying the effect of price.

Our bargaining model must identify $\tau$, $b$ and $\gamma$. Essentially, $\tau$ is identified by the extent to which MCOs value consumer surplus from hospital choice relative to payments to hospitals, which then is reflected in their negotiated equilibrium prices. The willingness-to-pay variables are (assumed exogenous) demand shifters that provide variation across MCOs, years and hospitals in valuations, and hence in expected equilibrium prices. The orthogonality condition between them and $\varepsilon$ will help identify $\tau$ by imposing the implications of the model as to equilibrium prices. The estimation of the $\gamma$ parameters is essentially a linear regression conditional on recovering marginal costs. Thus, identification here is straightforward conditional on identifying the other parameters. We believe that the bargaining weights have similar equilibrium implications to cost shifters and hence it would be difficult to identify the $b$ and $\gamma$ parameters at the same level, e.g., MCO fixed costs for bargaining weight and for marginal costs. Hence, when we include MCO fixed effects for bargaining weights we do not include these fixed effects for marginal costs.

4 Results

4.1 Summary Statistics

Table 1 presents the mean base prices for the set of hospitals used in the analysis. There is significant variation in risk-adjusted prices across the hospital prior to the merger. These differences do not reflect differences in case-mix, as our analysis controls for disease complexity with DRG weights. The range between the highest and lowest hospital is 36% of the mean
Table 1: Hospital characteristics

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Beds</th>
<th>Mean price $</th>
<th>FP</th>
<th>Mean NICU</th>
<th>Cath lab</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prince William Hospital</td>
<td>170</td>
<td>10,273</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Alexandria Hospital</td>
<td>318</td>
<td>9,754</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Fair Oaks Hospital</td>
<td>182</td>
<td>9,793</td>
<td>0</td>
<td>.5</td>
<td>1</td>
</tr>
<tr>
<td>Fairfax Hospital</td>
<td>833</td>
<td>11,881</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Loudoun Hospital</td>
<td>155</td>
<td>11,560</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Mount Vernon Hospital</td>
<td>237</td>
<td>12,110</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Fauquier Hospital</td>
<td>86</td>
<td>13,269</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>N. VA Community Hosp.</td>
<td>164</td>
<td>9,545</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Potomac Hospital</td>
<td>153</td>
<td>11,420</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Reston Hospital Center</td>
<td>187</td>
<td>9,972</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Virginia Hospital Center</td>
<td>334</td>
<td>9,545</td>
<td>0</td>
<td>.5</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: we report (unweighted) mean prices across year and payor.

PWH price, which is in the middle of the price distribution. Even within the Inova system there is notable vacation in prices with a range of $2,356 between the high (Mount Vernon) and low priced hospital (Alexandria). Inova Alexandria has two competitors located nearby, Virginia Hospital Center and Northern Virginia Community Hospital, although Northern Virginia Community Hospital closed after 2005.

Table 1 also presents other characteristics of the hospitals in HPD8 and Fauquier County. Hospitals are heterogeneous with respect to size, for-profit status and the degree of advanced services they provide. Seven of the eleven hospitals provided some level of neonatal intensive care services by the end of our sample, and most hospitals have cardiac catheterization laboratories which provide diagnostic and interventional cardiology services.

Table 2 presents summary statistics by hospital for the sample of patients we use to estimate the hospital demand parameters. They sample of patients is majority white at every hospital. Not surprisingly, there is significant variation in the mean DRG weight across hospitals. PWH’s mean DRG weight is 0.82 as reflective of their role as a community hospital. The patient-weighted mean DRG weight across all of Inova’s hospitals in 1.09 with its Fairfax and Mt. Vernon hospitals treating patients with the highest resource intensity.
Table 2: Patient sample

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Mean age</th>
<th>Share white</th>
<th>Mean DRG weight</th>
<th>Mean travel time</th>
<th>Mean coins. rate</th>
<th>Discharges</th>
<th>Total Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prince William Hospital</td>
<td>36.1</td>
<td>0.73</td>
<td>0.82</td>
<td>13.06</td>
<td>0.032</td>
<td>9,681</td>
<td>0.066</td>
</tr>
<tr>
<td>Alexandria Hospital</td>
<td>39.3</td>
<td>0.62</td>
<td>0.92</td>
<td>12.78</td>
<td>0.025</td>
<td>15,622</td>
<td>0.107</td>
</tr>
<tr>
<td>Fairfax Oaks Hospital</td>
<td>37.7</td>
<td>0.54</td>
<td>0.94</td>
<td>17.75</td>
<td>0.023</td>
<td>17,073</td>
<td>0.117</td>
</tr>
<tr>
<td>Fairfax Hospital</td>
<td>35.8</td>
<td>0.58</td>
<td>1.20</td>
<td>18.97</td>
<td>0.023</td>
<td>46,428</td>
<td>0.319</td>
</tr>
<tr>
<td>Loudoun Hospital</td>
<td>37.2</td>
<td>0.74</td>
<td>0.81</td>
<td>15.54</td>
<td>0.023</td>
<td>10,441</td>
<td>0.072</td>
</tr>
<tr>
<td>Mount Vernon Hospital</td>
<td>50.3</td>
<td>0.66</td>
<td>1.38</td>
<td>16.18</td>
<td>0.022</td>
<td>3,749</td>
<td>0.026</td>
</tr>
<tr>
<td>Fauquier Hospital</td>
<td>40.5</td>
<td>0.90</td>
<td>0.92</td>
<td>15.29</td>
<td>0.033</td>
<td>3,111</td>
<td>0.021</td>
</tr>
<tr>
<td>N. VA Comm. Hosp.</td>
<td>47.2</td>
<td>0.48</td>
<td>1.43</td>
<td>16.02</td>
<td>0.016</td>
<td>531</td>
<td>0.004</td>
</tr>
<tr>
<td>Potomac Hospital</td>
<td>37.5</td>
<td>0.60</td>
<td>0.93</td>
<td>9.62</td>
<td>0.024</td>
<td>8,737</td>
<td>0.060</td>
</tr>
<tr>
<td>Reston Hospital Center</td>
<td>36.8</td>
<td>0.69</td>
<td>0.90</td>
<td>15.35</td>
<td>0.021</td>
<td>16,007</td>
<td>0.110</td>
</tr>
<tr>
<td>Virginia Hospital Center</td>
<td>40.8</td>
<td>0.59</td>
<td>0.98</td>
<td>15.88</td>
<td>0.017</td>
<td>12,246</td>
<td>0.084</td>
</tr>
<tr>
<td>Outside option</td>
<td>39.3</td>
<td>0.82</td>
<td>1.39</td>
<td>0.00</td>
<td>0.029</td>
<td>2,113</td>
<td>0.014</td>
</tr>
<tr>
<td>All Inova</td>
<td>37.5</td>
<td>0.59</td>
<td>1.09</td>
<td>17.37</td>
<td>0.024</td>
<td>85,540</td>
<td>0.641</td>
</tr>
<tr>
<td>All others</td>
<td>38.1</td>
<td>0.68</td>
<td>0.92</td>
<td>13.74</td>
<td>0.023</td>
<td>60,199</td>
<td>0.359</td>
</tr>
</tbody>
</table>

About 1.4% of patients choose care in Virginia outside the geographic market. Patients choosing the outside option had a high mean DRG weight of 1.39 suggesting that they are traveling to specialized centers such as the University of Virginia Medical Center.

Table 2 also reveals heterogeneity in travel times. Notably, patients travel the furthest to be admitted at Inova Fairfax hospital, the largest hospital and only tertiary care hospital in our sample. Interestingly, Inova Fairfax also has the lowest average age of patient reflecting the popularity of its obstetrics program. Average coinsurance rates across hospitals range from 1.7 to 3.3%.

Finally, Table 2 provides the shares by discharges among hospital systems in this area. Within this market, Inova has a dominant share attracting 64% of the patients. PWH is the third largest hospital in the market with a 6.6% share. Using the standard *Horizontal Merger Guidelines* methodology, the 2006 HHI based on the relevant market is 4,428 and the proposed acquisition would have increased the HHI by 977 based on pre-merger shares.

A challenge for our model is explaining the large variation in the mean price that the
different MCOs pay hospitals. The highest-paying MCO pays hospitals, on average, over 100% more than the lowest paying MCO. While this variation is high, large variations across hospitals and payors is not uncommon (see Ginsburg, 2010). In our framework, there are two possible reasons for this variation, differences in bargaining weight and differential costs of treating patients across MCOs. We will estimate models that allow for both possibilities.

4.2 Patient choice estimates

We now exposit the results from our model of patient choice of hospital, based on equation (1). In addition to the negotiated price, the explanatory variables include hospital/year fixed effects, hospital indicators interacted with the patient’s DRG weight, and a rich set of interactions aimed at capturing the essential dimensions of hospital and patient heterogeneity that affect hospital choice.

Table 3 presents a selection of the coefficient estimates from the MNL model of hospital choice. Consistent with the large literature on hospital choice, we find that patients are very sensitive to travel times. The willingness to travel is increasing in the DRG weight and decreasing in age. The sensitivity to travel time is striking. An increase in travel time of 5 minutes reduces each hospital’s share between 17 and 41%. The parameter estimates imply that increasing the travel time to all hospitals by one minute reduces consumer surplus by approximately $167.

The parameter on out-of-pocket price is negative and significant indicating that, in fact, patients are sensitive to inpatient prices in their admission decision.\(^{21}\) However, in contrast to travel time, patients are relatively insensitive to the gross price paid from the MCO to the hospital, largely because of the low coinsurance rates that they face. Table 4 presents the estimated price elasticities of demand for selected hospitals. Own-price elasticities range from \(-0.098\) to \(-0.153\) across the five reported hospitals.

The fact that our elasticity estimates are substantially less than 1 imply that with Bertrand competition the observed prices could only be rationalized with negative marginal

\(^{21}\)Ho and Pakes (2011) find that in California, the patient’s hospital choice is also influenced by the prices paid by the MCOs.
Table 3: Multinomial logit demand estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base price x weight x coinsurance</td>
<td>-0.0008</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>Travel time</td>
<td>-0.1150</td>
<td>(0.0026)</td>
</tr>
<tr>
<td>Travel time squared</td>
<td>-0.0002</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Closest</td>
<td>0.2845</td>
<td>(0.0114)</td>
</tr>
<tr>
<td>Travel time x beds</td>
<td>-0.0118</td>
<td>(0.0008)</td>
</tr>
<tr>
<td>Travel time x age</td>
<td>-0.0441</td>
<td>(0.0023)</td>
</tr>
<tr>
<td>Travel time x FP</td>
<td>0.0157</td>
<td>(0.0011)</td>
</tr>
<tr>
<td>Travel time x teach</td>
<td>0.0280</td>
<td>(0.0010)</td>
</tr>
<tr>
<td>Travel time x res/beds</td>
<td>0.0006</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Travel time x income</td>
<td>0.0002</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Travel time x male</td>
<td>-0.0151</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>Travel time x age 60+</td>
<td>-0.0017</td>
<td>(0.0013)</td>
</tr>
<tr>
<td>Travel time x weight</td>
<td>11.4723</td>
<td>(0.4125)</td>
</tr>
<tr>
<td>Weight x beds</td>
<td>-0.8535</td>
<td>(0.1033)</td>
</tr>
<tr>
<td>Cardiac MDC x cath lab</td>
<td>0.2036</td>
<td>(0.0409)</td>
</tr>
<tr>
<td>Obstetric MDC x NICU</td>
<td>0.6187</td>
<td>(0.0170)</td>
</tr>
<tr>
<td>Nerv, circ, musc MDC x MRI</td>
<td>-0.1409</td>
<td>(0.0460)</td>
</tr>
</tbody>
</table>

N: 1,710,801
Pseudo R^{2}: 0.445

Note: specification also includes hospital-year interactions and hospital dummies interacted with disease weight.

** P < 0.01

Table 4: Mean estimated 2006 demand elasticities for selected hospitals

<table>
<thead>
<tr>
<th>Hospital</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>PW</td>
<td>Fairfax</td>
<td>Reston</td>
<td>Loudoun</td>
<td>Fauquier</td>
</tr>
<tr>
<td>1. Prince William</td>
<td>-0.125</td>
<td>0.052</td>
<td>0.012</td>
<td>0.004</td>
<td>0.012</td>
</tr>
<tr>
<td>2. Inova Fairfax</td>
<td>0.011</td>
<td>-0.141</td>
<td>0.018</td>
<td>0.006</td>
<td>0.004</td>
</tr>
<tr>
<td>3. HCA Reston</td>
<td>0.008</td>
<td>0.055</td>
<td>-0.149</td>
<td>0.022</td>
<td>0.002</td>
</tr>
<tr>
<td>4. Inova Loudoun</td>
<td>0.004</td>
<td>0.032</td>
<td>0.037</td>
<td>-0.098</td>
<td>0.001</td>
</tr>
<tr>
<td>5. Fauquier</td>
<td>0.026</td>
<td>0.041</td>
<td>0.006</td>
<td>0.002</td>
<td>-0.153</td>
</tr>
<tr>
<td>6. Outside option</td>
<td>0.025</td>
<td>0.090</td>
<td>0.022</td>
<td>0.023</td>
<td>0.050</td>
</tr>
</tbody>
</table>

Note: Elasticity is $\frac{\partial s_j}{\partial p_k s_j}$ (rows=$j$, col =$k$)
costs, even for stand-alone hospitals. The effective price sensitivity can of course be larger than the own-price sensitivity, but evaluating the extent to which this is the case requires estimating the bargaining model, which we now turn to.

### 4.3 Bargaining model estimates

Table 5 presents the coefficient estimates and standard errors from the second step of the estimation. We estimate two versions of the model. In Specification 1, we fix the bargaining weights to $b_{m(s)} = 0.5$ (which implies that $b_{s(m)} = 0.5$ also) and allow for marginal cost fixed effects for each hospital, MCO and year. In Specification 2, we allow the bargaining parameters to vary across MCOs (lumping MCO 2 and 3 together) but omit the MCO cost fixed effects. Both specifications also estimate the MCO welfare weight parameter, $\tau$. We bootstrap all standard errors at the level of the payor, year and system.

Focusing first on Specification 1, the point estimate on $\tau$ indicates that MCOs place over twice as much weight on enrollee welfare than implied by the MNL estimates, though the coefficient is not statistically significantly different from 0 or 1. A value of $\tau$ other than 1 may reflect employers placing a different weight on welfare than enrollees but may also be due to error in measuring coinsurance rates or physician incentives to steer patients to low-price hospitals (see Dickstein, 2011). The hospital cost parameters estimates show a large variation in the implied costs across the MCOs. This is not surprising as the cost differences will reflect variation in the data on mean hospital prices across the MCOs. There is also an increasing cost trend over time.

Turning to the results from Specification 2, here we estimate three different bargaining weights $b_{m(s)}$. We find significant variation in bargaining ability across the MCOs, with all MCOs having more leverage than hospitals. This variation is driven by the same price variation that generated the estimated cost heterogeneity in Specification 1. The estimates from Specification 2 imply that MCOs 2 and 3 have a bargaining weight of essentially 1, so that hospitals have a bargaining weight of essentially 0. Thus, MCOs 2 and 3 are able to drive down hospital surpluses down to their reservation values.
Table 5: Estimates from bargaining model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Specification 1</th>
<th>Specification 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>S.E.</td>
</tr>
<tr>
<td>MCO Welfare Weight ($\tau$)</td>
<td>2.79</td>
<td>2.87</td>
</tr>
<tr>
<td>MCO 1 Bargaining Weight</td>
<td>0.5</td>
<td>–</td>
</tr>
<tr>
<td>MCOs 2 &amp; 3 Bargaining Weight</td>
<td>0.5</td>
<td>–</td>
</tr>
<tr>
<td>MCO 4 Bargaining Weight</td>
<td>0.5</td>
<td>–</td>
</tr>
</tbody>
</table>

Cost Parameters

<table>
<thead>
<tr>
<th>Facility</th>
<th>Specification 1</th>
<th>Specification 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inova Fairfax</td>
<td>10,786</td>
<td>3,765</td>
</tr>
<tr>
<td>Inova Fair Oaks</td>
<td>11,192</td>
<td>3,239</td>
</tr>
<tr>
<td>Inova Alexandria</td>
<td>10,412</td>
<td>4,415</td>
</tr>
<tr>
<td>Inova Mount Vernon</td>
<td>10,294</td>
<td>5,170</td>
</tr>
<tr>
<td>Inova Loudoun</td>
<td>12,014</td>
<td>3,188</td>
</tr>
<tr>
<td>Prince William Hospital</td>
<td>8,635</td>
<td>3,009</td>
</tr>
<tr>
<td>Fauquier Hospital</td>
<td>14,553</td>
<td>3,390</td>
</tr>
<tr>
<td>No. VA Community Hosp.</td>
<td>10,086</td>
<td>2,413</td>
</tr>
<tr>
<td>Potomac Hospital</td>
<td>11,459</td>
<td>2,703</td>
</tr>
<tr>
<td>Reston Hospital Center</td>
<td>8,249</td>
<td>3,064</td>
</tr>
<tr>
<td>Virginia Hospital Center</td>
<td>7,993</td>
<td>2,139</td>
</tr>
<tr>
<td>MCO 2 Cost</td>
<td>–9,043</td>
<td>2,831</td>
</tr>
<tr>
<td>MCO 3 Cost</td>
<td>–8,910</td>
<td>3,128</td>
</tr>
<tr>
<td>MCO 4 Cost</td>
<td>–4,476</td>
<td>2,707</td>
</tr>
<tr>
<td>Year 2004</td>
<td>1,123</td>
<td>1,303</td>
</tr>
<tr>
<td>Year 2005</td>
<td>1,808</td>
<td>1,481</td>
</tr>
<tr>
<td>Year 2006</td>
<td>1,908</td>
<td>1,259</td>
</tr>
</tbody>
</table>

Note: we report bootstrapped standard errors at the payor, year, system level.
We believe that the results from Specification 1 are more reasonable and hence we focus on them in the rest of the paper. Figure 2 plots the predicted mean marginal costs \( (v_{mj}\gamma) \) against the actual estimated marginal costs \( (v_{mj}\gamma + \varepsilon_{mj}) \) using the Specification 1 estimates.\(^{22}\) It shows that the included cost shifters have a significant predictive effect as the two lines are highly positively correlated.

Figure 2: Scatterplot of predicted mean and actual estimated marginal cost

![Scatterplot Figure 2](image)

Figure 3 presents a scatterplot of the hospital/MCO base prices and the implied marginal costs. The vast majority of the observations are well above the 45 degree line indicating that most of the hospitals in our sample earn positive and meaningful margins. Table 6 lists the implied, mean 2006 Lerner Indices from Model 1 for each hospital and MCO in order to further quantify the visual information in Figure 3. Most hospitals are earning significant margins, with all mean margins exceeding 20%. Table 6 also shows the large variation in

\(^{22}\)We truncate negative actual marginal costs at zero.
Figure 3: Scatterplot of Hospital-MCO Base Prices on Implied Marginal Cost
the profitability of treating patients across MCOs. The margins from treating patients from MCO 2 and 3 are much larger than the margins from treating patients enrolled in either MCO 1 and 4.

Table 6: Estimated (unweighted) 2006 mean Lerner indices by hospital and payor

<table>
<thead>
<tr>
<th>Hospital/Payor</th>
<th>Lerner Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prince William Hospital</td>
<td>0.60</td>
</tr>
<tr>
<td>Alexandria Hospital</td>
<td>0.43</td>
</tr>
<tr>
<td>Fair Oaks Hospital</td>
<td>0.31</td>
</tr>
<tr>
<td>Fairfax Hospital</td>
<td>0.47</td>
</tr>
<tr>
<td>Loudoun Hospital</td>
<td>0.32</td>
</tr>
<tr>
<td>Mount Vernon Hospital</td>
<td>0.61</td>
</tr>
<tr>
<td>Fauquier Hospital</td>
<td>0.21</td>
</tr>
<tr>
<td>Potomac Hospital Corporation</td>
<td>0.48</td>
</tr>
<tr>
<td>Reston Hospital Center</td>
<td>0.45</td>
</tr>
<tr>
<td>Virginia Hospital Center</td>
<td>0.68</td>
</tr>
<tr>
<td>MCO 1</td>
<td>0.24</td>
</tr>
<tr>
<td>MCO 2</td>
<td>0.54</td>
</tr>
<tr>
<td>MCO 3</td>
<td>0.64</td>
</tr>
<tr>
<td>MCO 4</td>
<td>0.41</td>
</tr>
</tbody>
</table>

Note: Lerner index is \( \left( \frac{p_m - m_0}{p_m} \right) \).

Table 6 also allows us to back out the implied effective price elasticities using the inverse elasticity rule for single-hospital systems, \( elast_{m_j} = -Lerner^{-1} \). For Prince William Hospital, the inverse elasticity rule would imply an average price elasticity of \(-1.67\). In contrast, if patients faced the full cost of their treatment instead of having insurance, our first stage estimates imply that the price elasticity of demand for Prince William would be \(-4.98\), while Table 4 reports Prince William’s mean price elasticity as \(-0.125\). Thus, the effective price elasticities resulting from the bargaining model are part way between the actual price elasticity and the price elasticity without insurance. This implies that MCO bargaining leverage is a partial solution to the moral hazard problems inherent in healthcare insurance.
5 Counterfactuals

Table 7 presents the results from two counterfactual experiments. In the first experiment, we examine the implied impact of the merger between Inova and Prince William Hospital on predicted price, quantity and profit. In the second counterfactual we examine the impact of breaking up Inova and Loudoun Hospital on the same set of outcomes. The prices are weighted by hospital/MCO volume. We find that the PWH/Inova merger will lead to a significant increase in prices and profits for the new Inova system. The net price increase is approximately 4.3% and the net increase in profits is 12.7%. Quantity goes down only slightly, by 0.5%, reflecting both the fact that coinsurance rates are low (and hence that patient demand is inelastic) and the equilibrium increase in prices by rival hospitals. Managed care surplus, which is weighted consumer surplus net of payments to hospitals, drops by 34.5%.

Table 7: Counterfactuals: Prince William merger and Loudoun breakup

<table>
<thead>
<tr>
<th>System</th>
<th>%∆ Weight price</th>
<th>%∆ Quantity</th>
<th>%∆ Profits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counterfactual 1: Prince William and Inova merger</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inova &amp; PWH</td>
<td>4.3</td>
<td>−0.5</td>
<td>12.7</td>
</tr>
<tr>
<td>Rival hospitals</td>
<td>3.9</td>
<td>1.4</td>
<td>13.0</td>
</tr>
<tr>
<td>%∆ CS - MCO costs</td>
<td>−34.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Counterfactual 2: Breakup of Inova and Loudoun Hospital</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inova &amp; Loudoun</td>
<td>−1.1</td>
<td>0.1</td>
<td>−3.0</td>
</tr>
<tr>
<td>Rival hospitals</td>
<td>−0.1</td>
<td>0.1</td>
<td>−0.3</td>
</tr>
<tr>
<td>%∆ CS - MCO costs</td>
<td>6.4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The counterfactual predictions tell a quite different story for the Inova/Loudoun de-merger. Forcing a divestiture of Loudoun Hospital leads to a net reduction in price of 1.1% for the Inova system and a reduction in profits of 3.0%. The divestiture would increase net consumer surplus by 6.4%. The smaller impact is consistent with the Federal Trade Commission challenging Inova’s proposed Prince William acquisition but not its Loudoun acquisition.

In the Evanston Northwestern hospital merger case, the Federal Trade Commission imposed a remedy where they forced the Evanston Northwestern system to negotiate separately
with MCOs (with firewalls in place) from the newly acquired hospital, Highland Park Hospital.\textsuperscript{23} We examine the implications of this type of policy by simulating a world where the PWH negotiator bargains in a separate room from the other Inova hospitals. Thus, the PWH negotiator can only threaten the removal of PWH in a negotiation breakdown while the Inova negotiator can correspondingly only threaten the removal of the other Inova hospitals. We assume that the negotiators recognize their true incentives, namely that if they fail to negotiate a contract, some quantity will be diverted to hospitals that are part of the same system.

Table 8: Counterfactuals: conduct remedies for Prince William merger

<table>
<thead>
<tr>
<th>System</th>
<th>%Δ Weight price</th>
<th>%Δ Quantity</th>
<th>%Δ Profits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counterfactual 1: Base Prince William and Inova merger</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inova &amp; PWH</td>
<td>4.3</td>
<td>−0.5</td>
<td>12.7</td>
</tr>
<tr>
<td>Rival hospitals</td>
<td>3.9</td>
<td>1.4</td>
<td>13.0</td>
</tr>
<tr>
<td>%Δ CS - MCO costs</td>
<td>−34.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Counterfactual 3: PW and Inova merger with separate bargaining</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inova &amp; PWH</td>
<td>4.0</td>
<td>−0.6</td>
<td>10.6</td>
</tr>
<tr>
<td>Rival hospitals</td>
<td>2.8</td>
<td>1.4</td>
<td>9.4</td>
</tr>
<tr>
<td>%Δ CS - MCO costs</td>
<td>−31.1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 8 illustrates this counterfactual remedy. It replicates the results from the base Prince William Hospital experiment in Table 7 and presents results from a new experiment which imposes the conduct remedy. The conduct remedy performs much more similarly to the base merger outcomes than to the outcomes without a merger. It results in a slightly lower average price increase, 4.0% instead of 4.3%, and in a slightly higher net consumer surplus relative to the baseline. Overall, this remedy did not appear to re-inject competition into the marketplace. Thus, separate negotiations do not appear to be a solution to the problem of bargaining power by hospitals.

The Federal Trade Commission in its Evanston decision focused on the fact that this conduct remedy would re-inject competition into the market by reducing the leverage of the hospital.

\textsuperscript{23}In the Matter of Evanston Northwestern Healthcare Corporation, Docket No. 9315, Opinion of the Commissioners, 2008.
hospital that bargains separately; e.g., PWH could only threaten a small harm to the MCO from disagreement. However, this remedy also reduces the leverage of the MCO since if it threatens to walk from the PWH negotiation, some of its but-for PWH patients would certainly go to other Inova hospitals. The increase in disagreement values on both sides implies that the impact of this remedy is theoretically very ambiguous. Thus, it is not surprising that we find a very small effect empirically.

Table 9: Counterfactuals: No coinsurance

<table>
<thead>
<tr>
<th>System</th>
<th>%Δ Weight price</th>
<th>%Δ Quantity</th>
<th>%Δ Profits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counterfactual 4: No coinsurance relative to base</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inova &amp; PWH</td>
<td>3.4</td>
<td>-0.01</td>
<td>8.9</td>
</tr>
<tr>
<td>Rival hospitals</td>
<td>4.2</td>
<td>0.08</td>
<td>11.6</td>
</tr>
<tr>
<td>%Δ CS - MCO costs</td>
<td>6.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Counterfactual 5: PW and Inova merger w/ no coinsurance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Inova &amp; PWH</td>
<td>2.9</td>
<td>0</td>
<td>7.4</td>
</tr>
<tr>
<td>Rival hospitals</td>
<td>1.3</td>
<td>0</td>
<td>3.9</td>
</tr>
<tr>
<td>%Δ CS - MCO costs</td>
<td>-19</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Finally, we consider the impact of coinsurance rates, in Table 9. We find that Inova’s price would be 3.4% higher than in the base case if coinsurance rates were zero. The reason for this is because patient demand would go from having a moderate elasticity to no elasticity at all. Thus, both patient coinsurance and MCO bargaining leverage play a role in constraining prices in this market. In the case of no coinsurance, the impact of the Inova and PWH merger would be smaller than in the baseline, raising prices at the new Inova system only a further 2.9% relative to the base prices with no coinsurance.

6 Conclusion

Many bilateral, business-to-business transactions are between oligopoly firms negotiating prices over a bundle of imperfectly substitutable goods. In this paper we develop a model of the price negotiations game between managed care organizations and hospitals. We show that standard oligopoly models will generally not accurately capture the pricing behavior under
these bargaining scenarios. We then develop a simple GMM estimator of the negotiation process and estimate the parameters of the model using detailed managed care claims and patient discharge data from Northern Virginia. While our focus is on negotiations between hospitals and MCOs, we believe our framework can be applied in a number of alternative settings where there are a small number of “gatekeeper” buyers.

We find that patient demand is quite inelastic – with own-price elasticities of about 0.12 on average – due to the fact that patients typically only pay out-of-pocket 2 to 3 percent of the cost of their hospital care at the margin. Consistent with our theoretical model, prices are significantly constrained by the MCO bargaining leverage. Prices under MCO bargaining are still much higher than they would be in the absence of insurance. Without any out-of-pocket patient expenditures, prices would rise about 4% on average.

We further use our model to evaluate the impact of proposed hospital mergers on prices. We simulate the proposed merger between Inova hospital system and Prince William Hospital, which the FTC challenged. Our estimates indicate that the proposed merger would have significantly increased prices. We also use the model to simulate another merger that the FTC did not oppose and our estimates indicate that the merger had a small impact. The FTC has also turned to conduct remedies that allowed the merger to stand with each hospitals retaining separate, fire-walled negotiating teams. Our counterfactuals show that this remedy does not mitigate the harm of the transaction, because incentives change on both sides of the market.
References


Appendix A: Derivation of the $A$ term

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We defined the $A$ term as

$$\frac{\partial V_m}{\partial p_{mj}} = \tau \frac{\partial W(N_m, \vec{p}_m)}{\partial p_{mj}} - \frac{\partial TC_m(N_m, \vec{p}_m)}{\partial p_{mj}}$$  \hspace{1cm} (20)$$

$$W(N_m, \vec{p}_m) = \frac{1}{\alpha} \sum_{i=1}^{I_m} \sum_{d=1}^{D} f_{mid} \ln \left( \sum_{j \in N_m} e^{\delta_{mijd}} \right)$$  \hspace{1cm} (21)$$

$$\frac{\partial W(N_m, \vec{p}_m)}{\partial p_{mj}} = -\sum_{i=1}^{I_m} \sum_{d=1}^{D} c_{mid} w_{id} f_{mid} s_{mijd} \sum_{k \in N_m} e^{\delta_{mikd}} = -\sum_{i=1}^{I_m} \sum_{d=1}^{D} c_{mid} w_{id} f_{mid} s_{mijd}$$  \hspace{1cm} (22)$$

$$\frac{\partial TC_m(N_m, \vec{p}_m)}{\partial p_{mj}} = \sum_{i=1}^{I_m} \sum_{d=1}^{D} (1 - c_{mid}) f_{mid} w_{id} s_{mijd} + \sum_{i=1}^{I_m} \sum_{d=1}^{D} (1 - c_{mid}) f_{mid} w_{id} \sum_{k \in N_m} p_{km} \frac{\partial s_{mikd}}{\partial p_{mj}}$$  \hspace{1cm} (23)$$

Note that $\frac{\partial s_{mijd}}{\partial p_{mj}} = -\alpha c_{mid} w_{id} s_{mijd} (1 - s_{mijd})$ if $k = j$ and otherwise $\frac{\partial s_{mikd}}{\partial p_{mj}} = \alpha c_{mid} w_{id} s_{mikd} s_{mijd}$.

Putting this all together gives:

$$\frac{\partial V_m}{\partial p_{mj}} = -\tau \sum_{i=1}^{I_m} \sum_{d=1}^{D} c_{mid} w_{id} f_{mid} s_{mijd} - \sum_{i=1}^{I_m} \sum_{d=1}^{D} (1 - c_{mid}) w_{id} f_{mid} s_{mijd}$$

$$- \alpha \sum_{i=1}^{I_m} \sum_{d=1}^{D} (1 - c_{mid}) c_{mid} w_{id}^2 f_{mid} s_{mijd} \left( \sum_{k \in N_m} p_{km} s_{mikd} - p_{mj} \right).$$  \hspace{1cm} (24)$$
Appendix B: Derivation of the FOCs for the Prince William separate bargaining

For on-line publication

We start by considering the case where each hospital and MCO pair bargain in a separate room, even if the hospital is part of a system. Consider a system $s$ and a hospital $j \in J_s$. Define $NB^{m,j}(p_{mj}|p_{m,j},p_{m,s})$ to be the Nash bargaining product for this room. Analogously to (10), we have:

$$NB^{m,j}(p_{mj}|p_{m,j},p_{m,s}) = 
\left( q_{mj}(N_m,p^m_{m})[p_{mj} - mc_{mj}] + \sum_{k \in J_s, k \neq j} (q_{mk}(N_m,p^m_{m}) - q_{mk}(N_m \setminus j,p^m_{m}))[p_{mk} - mc_{mk}] \right)^{b_{s(m)}}$$

$$\left( V_m(N_m,p^m_{m}) - V_m(N_m \setminus j,p^m_{m}) \right)^{b_{m(s)}}. \quad (25)$$

In words, the threat point of system $s$ in this room is now that it withdraws hospital $j$. In this case, it will lose its profits from hospital $j$ but will gain profits from the additional diversion quantity $\lambda_{mjk} \equiv (q_{mk}(N_m \setminus j,p^m_{m}) - q_{mk}(N_m,p^m_{m}))$ from each other hospital $k \neq j$ that it owns. The MCO’s threat point from failure in this room is now the difference in value from losing hospital $j$ instead of from losing system $s$.

Analogously to (12), the FOC for this problem is:

$$b_{s(m)} \frac{q_{mj} + \sum_{k \in S_j} \frac{\partial q_{mk}}{\partial p_{mj}}[p_{mk} - mc_{mk}]}{q_{mj}(N_m,p^m_{m})[p_{mj} - mc_{mj}] - \sum_{k \in J_s, k \neq j} \lambda_{mjk}[p_{mk} - mc_{mk}] - \sum_{k \in J_s, k \neq j} \lambda_{mjk}[p_{mk} - mc_{mk}]}$$

$$= -b_{m(s)} \frac{\partial V_m}{\partial p_{mj}} \left( V_m(N_m,p^m_{m}) - V_m(N_m \setminus j,p^m_{m}) \right). \quad (26)$$

We now consider the case where Inova acquires Prince William but where Prince William bargains separately from the rest of the Inova system. In this case, the FOCs for the Prince
William bargaining rooms will be exactly as in (26). The FOCs for the other Inova hospitals will now resemble (26) but the threat points will reflect removing all Inova legacy hospitals from the network and having diversion quantities only for Prince William.

Appendix C: Computation of equilibrium prices when coinsurance is zero

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This appendix details the closed-form solution for the zero coinsurance case. As noted in Section 2.3, equilibrium prices for hospitals within a system are not unique, and it is only meaningful to consider system revenue. Here, for ease of exposition we solve for the case where each system has the same price across its hospitals for system $s$, which we denote $\overline{p}_{ms}$.

We start with (17), which is the FOC for system $s$ and MCO $m$, substitute in the system price, and expand to make explicit the dependence on prices for other systems. We obtain:

$$\overline{p}_{ms} \sum_{k \in J_s} q_{mk}(N_m) - \sum_{k \in J_s} mc_{mk} q_{mk}(N_m) = \frac{b_{s(m)}}{b_{m(s)}} \left[ \tau (W_m(N_m) - W_m(N_m \setminus J_s)) + \sum_{r=1}^{S} \sum_{k \in J_r} (q_{mk}(N_m \setminus J_s) - q_{mk}(N_m)) + p_{m0} (q_{m0}(N_m \setminus J_s) - q_{m0}(N_m)) \right],$$

(27)

where we have eliminated the dependence of $q$ on price, given the lack of coinsurance.

Define $\theta_{ms} = \frac{b_{m(s)}}{b_{s(m)}}$, $\overline{mc}_{ms} = \frac{\sum_{k \in J_s} mc_{mk}(N_m)q_{mk}(N_m)}{\sum_{k \in J_s} q_{mk}(N_m)}$, $d_{msr} = \frac{\sum_{k \in J_r} (q_{mk}(N_m \setminus J_s) - q_{mk}(N_m))}{\sum_{k \in J_s} q_{mk}(N_m)}$, and $d_{ms0} = \frac{q_{m0}(N_m \setminus J_s) - q_{m0}(N_m)}{\sum_{k \in J_s} q_{mk}(N_m)}$. Recall that the prices of the outside alternative, $p_{m0}$ are exogenously determined. Rearranging terms from (27) so that the endogenous prices are on the left side, and noting that $q_{mk}(N_m \setminus J_s) = 0$ for hospitals $k$ owned by system $s$, we obtain:

$$(1 + \theta_{ms})\overline{p}_{ms} - \sum_{r \neq s=1}^{S} d_{msr} \overline{p}_{mr} = \tau \left( \frac{W_m(N_m) - W_m(N_m \setminus J_s)}{\sum_{k \in J_s} q_{mk}(N_m)} \right) + \theta_{ms}\overline{mc}_{ms} + d_{ms0}p_{m0}. \quad (28)$$
Expressing (28) in matrix form and solving for prices yields:

\[
\begin{bmatrix}
p_{m1} \\
p_{m2} \\
\vdots \\
p_{mS}
\end{bmatrix}
= \mathbf{M}^{-1} \begin{bmatrix}
\frac{W_m(N_m) - W_m(N_m \setminus J_1)}{\sum_{k \in J_1} q_{mk}} \\
\frac{W_m(N_m) - W_m(N_m \setminus J_2)}{\sum_{k \in J_2} q_{mk}} \\
\vdots \\
\frac{W_m(N_m) - W_m(N_m \setminus J_S)}{\sum_{k \in J_S} q_{mk}}
\end{bmatrix}
+ \begin{bmatrix}
\theta_{m1} \overline{mc}_{m1} \\
\theta_{m2} \overline{mc}_{m2} \\
\vdots \\
\theta_{mS} \overline{mc}_{mS}
\end{bmatrix}
+ \begin{bmatrix}
d_{m10} p_{m0} \\
d_{m20} p_{m0} \\
\vdots \\
d_{mS0} p_{m0}
\end{bmatrix}
\]  

(29)

where

\[
\mathbf{M} \equiv \begin{bmatrix}
(1 + \theta_{m1}) & -d_{m12} & \ldots & -d_{m1S} \\
-d_{m21} & (1 + \theta_{m2}) & \ldots & -d_{m2S} \\
\vdots & \vdots & \ddots & \vdots \\
-d_{mS1} & -d_{mS2} & \ldots & (1 + \theta_{mS})
\end{bmatrix}
\]

Given estimates of \(\{\theta_{ms}\}_{s=1}^{S}, \tau\), the cost parameters, and the net diversion quantities \(d\), (29) allows us to compute equilibrium prices for any industry structure with a simple matrix inverse. In the paper, we employ (29) to compute equilibria for actual and counterfactual market structures with zero coinsurance.