Abstract: Several recent papers estimate discrete choice models in hospital markets, and then use those estimates to generate a hospital-by-hospital measure of market power. They then use these market power measures as an independent variable in hospital price regressions. The estimated relationship between market power and price is then used to simulate the effects of mergers. In this paper, we seek to test the accuracy of these methods. To do this, we set up a simple model of hospital competition which can, for any given values of the parameters of the model generate the “true” effects of a merger between any two hospitals. These true effects are then compared to the effects that would be predicted by the simulation model described above, using only the “data” (pre-merger prices and consumer choice information) that would be observed by a researcher. We repeat this exercise for a large number of simulated markets and, using each of several commonly used market power measures, derive results regarding the conditions under which the simulations do or do not accurately predict hospital merger effects. The results suggest that each of the market power measures slightly underpredicts merger effects, on average, and that this underprediction becomes more pronounced as the diversion between the merging hospitals increases.

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I. Introduction

In recent years evidence has mounted that some hospital mergers have resulted in substantial price increases.\(^1\) As a consequence, researchers have become interested in developing new methods of predicting the hospital merger effects. These new methods involve some variation on the theme of a price-concentration analysis, in which hospital prices are regressed on a measure of market power that is derived from patient discharge data (i.e., data on which consumers chose which hospitals). These estimates of the effect of market power on price are then used to generate a prediction regarding the effect of a merger on prices. The purpose of this paper is to make a contribution to evaluating the accuracy of these simulation methods.

One obvious way to test these methods would be to gather data on a large number of actual hospital mergers, apply the methods to pre-merger data, generate predictions of the merger effects, then use post-merger data to measure the actual effects of each merger, and then compare. The problem with such an exercise is its scope: gathering good data on a sufficient number of mergers that such a test would have statistical power would be a very daunting task. This problem is made worse by the fact that the best available price data, which is data on actual transaction prices, is generally proprietary and unavailable to researchers.\(^2\)

In this paper, we take a different approach. Instead of gathering data on a large number of hospital mergers, we randomly generate our own “data” on the attributes of hospitals (geographical location and hospital fixed effects) and on patient attributes and preferences (location, the degree of their distaste for travel, and idiosyncratic preferences for each hospital). We then set up a Nash bargaining game between each hospital and a monopoly managed care organization (MCO). We solve the game for the equilibrium prices of each hospital and for the MCO’s profit-

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maximizing premium for its insurance product, given the pre-merger market structure. We then change the market structure by merging two of the hospitals and re-solve the game for the new equilibrium prices. The difference between the two sets of prices represents what we call the “true” merger effect.

We then take the “data” that would be available to a hypothetical econometrician (pre-merger prices and patient flows) and apply each of the merger simulation methods. This generates predicted merger effects, which can then be compared to the “true” effects. The closer the match, the more accurate the methods can be said to be.

II. Concentration Measures:

Traditionally, concentration measures in price-concentration studies were derived by delineating geographic markets, and then calculating concentration in each market using the Herfindahl-Hirschman Index ($HHI$). This is problematic, as the “correct” way to define geographic market is generally highly contentious.\(^3\) More recently, researchers have developed new concentration measures that have the attractive property that no such \textit{a priori} market definition is necessary. Instead, the scope of geographic competition is determined by the data themselves.\(^4\) We consider two classes of concentrations measures: Willingness-to-Pay ($WTP$) and Hospital-Specific $HHIs$ ($HSHHIs$). In the remainder of this section, we briefly discuss each of these measures.

\(^2\) The alternative, which is used by most academic researchers, is to use publicly available “billed charges” data and then to estimate price by multiplying these charges by the publicly available “cost-to-charge” ratios.

\(^3\) Economists have generally preferred to avoid geographic market exercises when alternatives are available, as these exercises have the unappealing feature that all firms that are found to be “in” the market are treated as equally competitively significant, and firms that are found to be “out” of the market are treated as if they do not exist.
A. Willingness-to-Pay (WTP).

The first concentration measure we consider is the “Willingness-to-Pay” (WTP) measure developed Town & Vistnes (2001) and by Capps, Dranove, and Satterthwaite (2003). Although Capps, Dranove, and Satterthwaite (CDS) were the first to apply the term “Willingness-to-Pay” to this competition measure, the approach developed by Town and Vistnes (TV) is very similar and, as will be discussed below, the differences that do exist are irrelevant for our study.

WTP attempts to capture the value-added of a hospital or system to a payer’s provider network. It evaluates this value-added at the individual level using inpatient discharge data and then aggregates up to the level of a hospital or system by integrating over the (usually empirical) distribution of observed consumer characteristics.

Consider a standard discrete choice problem is which consumer preferences over some set \( G \) are given by:

\[
U_{ij} = V_{ij} + \varepsilon_{ij}, \quad \forall j \in G
\]

where \( V_{ij} \) is a linear-in-parameters index of hospital characteristics, and interactions of hospital and consumer characteristics, and \( \varepsilon_{ij} \) is an independently and identically distributed extreme value error term. WTP considers the valuation of the set \( G \) for consumer \( i \) at a point before the idiosyncratic components are revealed to the consumer. Hence, it utilizes the expected value of the maximum where expectations are taken over the joint distribution of the extreme value errors. This has the well-known result:

\[
E_{\varepsilon} [\text{MAX}_{j \in G} \{V_{ij} + \varepsilon_{ij}\}] = \gamma + \ln \sum_{j \in G} e^{V_{ij}}
\]

\(^4\) In other words, a disagreement about whether a particular hospital is competitively significant can be resolved directly by simply including that hospital in the calculation of the concentration measure. The hospital is competitively significant if and only if its inclusion causes a significant change in the concentration measure.
where \( \gamma \equiv E[E_{ij}] \), which is known as Euler’s constant (approximately 0.5772) and is the mean of the unconditional Extreme Value distribution.

TV construct a hospital- or system-specific competition measure from this by evaluating this expectation over the choice set that excludes the specific hospital or system and then aggregates across consumers. Hence, TV define the mean expected welfare to a payer’s enrollees for the network that excludes hospital \( k \) as:

\[
W_{G^k} = \frac{1}{N} \sum_i \ln \sum_{j \in G^k} \exp\{V_{ij}\}
\]

where \( N \) denotes the number of patients covered by the payer. TV hypothesize that \( W_{G^k} \) should be negatively related to prices, ceteris paribus.

In contrast, CDS define the WTP of person \( i \) for hospital \( k \) as the difference between the expected value of the max over the full choice set and the expected value of the max over the set that excludes \( k \). Hence:

\[
WTP_{ik} = \left\{ \gamma + \ln \sum_{j \in G} e^{V_{ij}} \right\} - \left\{ \gamma + \ln \sum_{j \in G^k} e^{V_{ij}} \right\} = \ln \left( \frac{\sum_{j \in G} e^{V_{ij}}}{\sum_{j \in G^k} e^{V_{ij}}} \right) = \ln \left( \frac{1}{1 - prob_{ik}} \right)
\]

where

\[
prob_{ik} = \Pr[U_{ik} > U_{ij}, \forall j \neq k] = \frac{e^{V_{ia}}}{\sum_{j} e^{V_{ij}}}.
\]

So the willingness-to-pay of consumer \( i \) for hospital \( k \) is a straightforward function of \( prob_{ik} \), which comes directly out of the choice model in (1) above. The WTP for hospital \( k \) is the expected value of (5) where expectations are taken over the joint distribution of consumer characteristics: demographics, clinical conditions, and location. That is:
where $X_i$ denotes the vector of consumer characteristics, $F(X_i)$ denotes the population distribution, and $prob_{ik}$ is understood to be a function of $X_i$.

In practice, $WTP_k$ is usually evaluated by treating the observed discharge data as a random draw from $F(X_i)$. Hence:

(6) \[ WTP_k \approx \sum_i \ln \left( \frac{1}{1 - prob_{ik}} \right) \]

CDS hypothesize that $WTP_k$ should be positively related to prices, ceteris paribus.

The willingness-to-pay measures defined in (3) and (6) are hospital-level measures since they are determined solely by the valuation of the choice set that excluded a given hospital only. As such, it is not affected by the industry market structure, and therefore, cannot be the basis for simulating a merger. However, defining (3) and (6) at the system level is a straightforward generalization. In TV, the mean expected welfare for a given system is defined at the network that excludes the entire system. Similarly, in CDS, the relevant $WTP$ evaluates the value-added of the entire system. Hence, for system $s$,

(7) \[ W_{G,s} = \frac{1}{N} \sum_i \ln \left( \sum_{j \in G\backslash s} \exp \{V_{ij}\} \right) \]

and

(8) \[ WTP_s = \sum_i \ln \left( \frac{1}{1 - \sum_j prob_{ij}} \right) = \sum_i \ln \left( \frac{1}{1 - PROB_{is}} \right). \]
As defined above, $W_{G,k}$ and $WTP_k$ are simply linear transformations of one another. However, there are a number of differences in how these measures are defined in TV and CDS. In most instances, these differences are irrelevant for this study and so we summarize them in the appendix. However, there is one distinction between TV and CDS is more substantive and lies in how they define merger effects in their competition measures. Consider a merger between hospitals $k$ and $l$. TV define the increase in bargaining power for $k$ as the change in mean expected welfare for hospital $k$:

$$\Delta W_{G,k} = W_{G,k} - W_{G,k,l}$$

$$= \frac{1}{N} \sum_i \ln \left( \frac{1}{1 - prob_{ik} - prob_{il}} \right) - \frac{1}{N} \sum_i \ln \left( \frac{1}{1 - prob_{ik}} \right)$$

$$= \frac{1}{N} \sum_i \ln \left( \frac{1 - prob_{ik}}{1 - prob_{ik} - prob_{il}} \right)$$

In the TV definition, the change in bargaining power is the simple change in the relevant right hand side variable. The change in bargaining power is different for $k$ and $l$, and, generally, the increase in bargaining power is inversely related to relative pre-merger bargaining power.

In contrast, CDS consider the difference between the $WTP$ of the merged system and the sum the pre-merger $WTP$s. Hence,

$$\Delta WTP_k = WTP_{k,l} - WTP_k - WTP_l$$

$$= \sum_i \ln \left( \frac{1}{1 - prob_{ik} - prob_{il}} \right) - \sum_i \ln \left( \frac{1}{1 - prob_{ik}} \right) - \sum_i \ln \left( \frac{1}{1 - prob_{il}} \right)$$

$$= \sum_i \ln \left( \frac{(1 - prob_{ik})(1 - prob_{il})}{1 - prob_{ik} - prob_{il}} \right).$$

In the CDS definition, the change in bargaining power is defined at the post-merger system level and there appears to be no well-defined way to back out different price effects for $k$ and $l$. However, the CDS definition has the intuitive property that the change in bargaining power is close to
zero if consumers do not view $k$ and $l$ as substitutes, i.e., $prob_{ik} < d$ or $prob_{il} < d$ from some positive $d$ arbitrarily close to zero for all $i$. The TV definition does not have this intuitive property.

In this study, we consider both approaches. That is, we regress prices on the CDS measure $WTP$ and evaluate the predicted price changes based on the changes in bargaining power in (9) and (10). In the CDS definition, we simply assume that the predicted price increase will be the same for both $k$ and $l$.

Two final notes on both the TV and CDS versions of $WTP$ should be made. First, both have the counterintuitive property that the bargaining power measures do not change for non-merging hospitals. Hence, the models predict no price effect for these hospitals even if they are close competitors of the merging firms. Second, as suggested in formulas (7) and (8), the bargaining power of the system is based on its threat to exclude the entire system. Hence, “all-or-nothing bargaining” while not explicitly considered in TV or CDS, is nonetheless an important component in how their bargaining power measures are defined.

A problem with using $WTP$ as the concentration measure is that it mechanically assigns a high willingness-to-pay to large hospital systems purely by virtue of their size. That is, the price regressions will have a poor fit if there is not a strong relationship between system size and prices. Of course, there may in fact be a strong relationship between size and prices, whether because higher quality hospitals attract more patients and also have higher prices, or because hospitals in multi-hospital systems may already be merged with some of their would-be competitors. On the other hand, this relationship may not be very strong.\(^5\) If large hospital systems are not composed of hospitals of particularly high quality, and/or if they are not composed of hospitals that are close competitors, then the relationship might be relatively weak. Furthermore, it is entirely pos-

\(^5\) For evidence of this, see Sorensen (2003).
sible for small independent hospitals to command higher prices than do nearby multi-hospital systems by virtue of some feature such as a desirable location.

An alternative specification of willingness-to-pay that addresses this problem is to define a “per-person” WTP (denoted by WTP_PP) which is equal to:

(11) \[ WTP_{PP} = \frac{WTP_s}{\sum_i PROB_{is}} \]

That is, the WTP_PP is simply the WTP divided by the predicted total consumers who choose system s. This has the effect of assigning willingness to pay on the basis of consumer valuation of the hospital’s characteristics, rather than by the sheer size of the system.

B. Hospital-Specific HHIs (HSHHIs).

An alternative measure of concentration is known as Hospital-Specific HHI, and is used by Capps & Dranove (2004) and Melnick & Keeler (2007). As with the WTP measures, the first step is to estimate a choice model like (1) and then derive, for each consumer, the probability of choosing each hospital. With this in hand, it is possible to regard each consumer as a “market” with “shares” that correspond to the choice probabilities.\(^6\) It is then possible to calculate an HHHI for each consumer using the familiar formula:

(12) \[ HHHI_i = \sum_j \text{prob}_{ij}^2 \]

We refer to the measure in (12) as HHHI, because it is calculated using “hospital probabilities,” meaning that it ignores any joint ownership of hospitals. Below this will be contrasted with SHHI, which is calculated using “system probabilities.”

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\(^6\) An alternative to treating each patient as a “market” is to divide the patient population into discrete “bins” (for example a bin could be a zip-code/diagnostic code combination), and then to apply (12) and (13) to these bins. This is the actual approach taken by Capps & Dranove (2004) and by Melnick & Keeler (2007).
Having calculated the $HHHI_i$ for each consumer $i$, the next step is to calculate $HSHHI_j$ for each hospital. This is done by calculating a weighted sum of the $HHHI_i$s, where the weights are defined as follows: the weight given to consumer $i$ in calculating the $HSHHI_j$ for hospital $j$ is equal to the total contribution of consumer $i$ to hospital $j$’s total expected patients. That is:

$$HSHHI_j = \sum_i \frac{prob_{ij}}{\sum_j prob_{ij}} HHHI_i$$

The intuitive interpretation of an $HSHHI$ is that a hospital for which a large proportion of its patients are drawn from consumers with high $HHHI$s can be thought of as operating in a generally concentrated environment, and vice-versa.7

The $HSHHI$ definition described above is applicable if all hospitals are independent, and must be modified if some hospitals are part of multi-hospital systems. That is, “System-Specific $HHIs$” ($SSHHIs$) must be calculated instead. These $SSHHIs$ can be calculated in one of two ways. Both begin by calculating the individual-specific $HHIs$ in a manner similar to (12), but these use the system shares $PROB_{is}$ and are denoted $SHHI_i$ in contrast to the $HHHI_i$s that used individual hospital shares $prob_{ij}$. That is:

$$SHHI_i = \sum_s PROB_{is}^2$$

Like the $HSHHI$s, the $SSHHI$s are calculated by taking a weighted average of the individual-specific $HHIs$. The weights can either be the system weights or the individual hospital weights. If hospital weights are used, then the $SSHHI_s$ for hospital system $s$ is calculated as:

$$SSHHI_s = \sum_i \frac{prob_{ij}}{\sum_j prob_{ij}} SHHI_i$$

7 The $HSHHI$ is constructed in such a way that a difference of opinion about whether a particular type is competitively significant can be resolved by simply including data from that type in the analysis. The type is competitively significant if and only if its inclusion causes the $HSHHI$s to change substantially for the hospitals of interest.
If system weights are used, then the $SSHHI_s$ are calculated as:

$$(15b) \quad SSHHI_s = \sum_i \sum_{i} PROB_{is} PROB_{ij} \cdot SHHI_i$$

If system weights are used, then the $SSHHI_s$ will be the same for all of the hospitals in a system, whereas this is not the case if the hospital weights are used.

Having calculated the $SSHHI_j$s, the next step is to estimate the price-concentration equation. The simplest version of this equation is:

$$(16) \quad price_j = \phi_0 + \phi_1 SSHHI_j + \xi_j$$

One advantage of the $SSHHI$ approach is that, unlike in the case of $WTP$ above, a merger effects the $SSHHI$, and hence the predicted price, of the non-merging hospitals.

III. The Bargaining Model:

A. Setup.

There is a set of hospitals $G$ with a cardinality of $g$. A monopoly managed care organization (MCO) enters into separate and simultaneous bargaining with each hospital in $G$. A deal between the MCO and a hospital, if a deal is reached, consists of a linear per-patient price. With its network and its negotiated prices in place, the MCO sets the profit-maximizing premium for its insurance product. Given this premium, consumers choose whether to purchase insurance from the MCO. Consumers who purchase insurance become sick with some probability, and seek care at their most preferred hospital in the MCO’s network (people with no insurance do not use any hospital). For convenience, we set this probability equal to one, in order to abstract from the issue of risk-aversion. The MCO, as we model it, is an assembler of a network and not an insurer. The out-of-pocket costs faced by consumers are the same for all hospitals in the network, regard-
less of the price negotiated with each hospital by the MCO. In other words, the MCO cannot “steer” consumers by giving them incentives to use hospitals with which the MCO has a lower contracted price.

B. Bargaining.

Prices are set by $G$ separate Nash bargains: each of the $g$ hospitals in $G$ has a separate negotiation with a representative of the MCO. Negotiation proceeds under the standard Nash assumptions that: (i) all negotiations happen simultaneously; (ii) no party to any negotiation observes or is in any way affected by what happens in any of the other negotiations; (iii) both parties to each negotiation believe that all the other negotiations will be successful (i.e., that all other hospitals will be included in the MCO’s network); and (iv) both parties to each negotiation have beliefs (which turn out to be correct in equilibrium) about the prices agreed to in the other negotiations.

The bargaining equation between the MCO and an independent hospital $k$ is as follows:

$$\max_{\text{price}_k} \left[ (n_k^G (\text{price}_k - c) - 0)^{\alpha} \left( \sum_{j \in G} n_j^G (\text{prem}_j - \text{price}_j) - \sum_{j \in G \setminus k} n_j^{G \setminus k} (\text{prem}_j^{G \setminus k} - \text{price}_j) \right)^{1-\alpha} \right]$$

As is standard in Nash bargaining, the equilibrium negotiated price for hospital $k$ ($\text{price}_k$) is the product of the increase in hospital $k$’s payoff if a deal is reached times the increase in the MCO’s payoff if a deal is reached.\(^8\) The payoff to hospital $k$ if it reaches a deal with the MCO is $n_k^G (\text{price}_k - c)$, where $G$ represents the complete set of hospitals or the “network of the whole,” and $n_k^G$ is the expected number of consumers who buy insurance and choose hospital $k$ when the

\(^8\) An equivalent way to describe the solution to a Nash Bargaining game is to identify the total joint surplus accruing to the parties if a deal is reached, and then splitting that deal-specific joint surplus between the two parties according to the bargaining power of each side (i.e., the hospital would get a share $\alpha$ and the MCO would get a share $1-\alpha$). The joint surplus from reaching a deal is equal to: (hospital’s payoff if a deal is reached – hospital’s payoff if no deal is reached) + (MCO’s payoff if a deal is reached – MCO’s payoff if no deal is reached).
network offered by the MCO is the network of the whole, and \( price_k \) is the price that hospital \( k \) negotiates with the MCO. The payoff to hospital \( k \) if it fails to reach a deal with the MCO is zero. The parameter \( a \) represents the bargaining power of the hospital, and \((1-a)\) represents the bargaining power of the MCO.

The payoff to the MCO if it reaches a deal with hospital \( k \) is as follows. Since, by assumption, both parties to the negotiation believe that all the other hospitals will be in the MCO’s network, the premium if a deal is reached between the MCO and hospital \( k \) will be \( prem^G \), which is the premium that maximizes the MCO’s profits given that its network is the network of the whole. For each hospital \( j \in G \) in the network of the whole, there are \( n^G_j \) consumers who buy insurance and choose hospital \( j \), and each of these consumers will generate a profit for the MCO of \( prem^G \) minus hospital \( j \)’s price \( price_j \). Similarly, the payoff to the MCO if it fails to reach a deal with hospital \( k \) is as follows. \( G \setminus k \) represents the set of all hospitals except \( k \). For each hospital \( j \in G \setminus k \) in the network, there are \( n^{G \setminus k}_j \) consumers who buy insurance and choose hospital \( j \). For each of these consumers, the MCO receives a margin equal to \( prem^{G \setminus k} \) (which will be lower than \( prem^G \)) minus the negotiated price \( price_j \).

The above discussion raises the question of where the optimal premium \( prem^G \) comes from. It is a function of the prices reached in the negotiations with all the other hospitals, and of consumer preferences. The reason is that any given candidate premium will cause a certain number of people to buy insurance, and these buyers will distribute themselves among the different hospitals according to their preferences.\(^9\) Since each of the other hospitals has its own price, and hence its own profit margin, the profits of any candidate premium will depend on those prices,

\(^9\) Recall the assumption that the out-of-pocket costs of all the hospitals are the same.
on who will or will not buy insurance at that premium, and on which hospital the insured patients will choose to use.

C. Insurance Premiums.

The valuation of patient $i$ for insurance coverage is determined as follows. Following TV and CDS, we assume that consumers do not know the realization of their idiosyncratic preference shocks when they are buying insurance. Rather, they know the distribution of those shocks, and their valuation for insurance is equal to the expected value of the maximum of the utilities from using each hospital, which is equal to $\gamma + \ln \sum_j e^{V_j}$. This valuation is still in utils, and must be converted to dollars, which we do as follows:

$$Valuation_i = \lambda_1 + \lambda_2 \ln \sum_j e^{V_j} + \zeta_i$$

where $\zeta_i$ denotes an idiosyncratic component of insurance valuation. This component is also assumed to be distributed Type 1 Extreme Value and is assumed to be unknown to both the MCO and hospital during bargaining. Hence, the MCO calculates the $g+1$ optimal premiums for a candidate vector of prices taking expectations over the distribution of both idiosyncratic component, $\zeta_i$ and $\epsilon_{ij}$. This seems to be a reasonable approach in that the MCO will not know exactly who will buy insurance and who will go to which hospital when the bargaining is taking place. Additionally, the idiosyncratic component $\zeta_i$ also ensures that the MCO’s objective function is differentiable in the premiums in that it avoids the use of step functions. This simplifies solving the MCO’s optimization problem significantly without sacrificing any basic intuition.
The MCO’s optimal premium will depend on the probabilities of patient insurance take-up and hospital choices of the marginal patient. Specifically, the MCO solves the maximization problem:

\[
(19) \quad \max_{\text{prem}^G} \left\{ \sum_i \left[ \left( \text{prem}^G - \sum_j \text{price}_j \text{prob}^G_{ij} \right) \left( 1 + \exp \left\{ \text{prem}^G - \lambda_1 - \lambda_2 \ln \sum_{j \in G} e^G_{ij} \right\} \right) \right] \right\}.
\]

The interpretation of (19) is as follows. For a candidate premium \( \text{prem}^G \), the first term in the parentheses represents the expected margin that the MCO will receive for patient \( i \). This margin will only be realized conditional on patient \( i \) actually purchasing insurance (i.e., having a valuation greater than the premium). Since the MCO does not know the idiosyncratic component \( \zeta_i \), the MCO takes expectation over its distribution and multiplies the expected margin by the probability of insurance take-up (the term in the second parentheses). The expected number of patients who use hospital \( j \) is equal to:

\[
(20) \quad n^G_j = \sum_i \text{prob}^G_{ij} \left( 1 + \exp \left\{ \text{prem}^G - \lambda_1 - \lambda_2 \ln \sum_{j \in G} e^G_{ij} \right\} \right)^{-1}.
\]

Similarly, for a given hospital \( k \), the MCO finds the premium that maximizes its profit if hospital \( k \) is excluded by solving:

\[
(21) \quad \max_{\text{prem}^{G,k}} \left\{ \sum_i \left[ \left( \text{prem}^{G,k} - \sum_j \text{price}_j \text{prob}^{G,k}_{ij} \right) \left( 1 + \exp \left\{ \text{prem}^{G,k} - \lambda_1 - \lambda_2 \ln \sum_{j \in G \backslash k} e^G_{ij} \right\} \right) \right] \right\}
\]

where \( \text{prob}^{G,k}_{ij} \) denotes the probability that patient \( i \) would choose hospital \( j \) given that hospital \( k \) was not available. Note that in this case, the marginal valuations are taken over the choice that excludes hospital \( k \):

\[
(22) \quad \text{Valuation}^G_{i,k} = \lambda_1 + \lambda_2 \ln \sum_{j \in G \backslash k} e^G_{ij} + \zeta_j.
\]
The expected number of patient admitted to hospital $j$ under the exclusion of hospital $k$ is defined as:

\begin{equation}
 n_{G,j}^{G,k} = \sum_{i} prob_{G,j}^{G,k} \left( 1 + \exp \left( prem_{G,j}^{G,k} - \lambda_1 - \lambda_2 \ln \sum_{l \in G,k} e^{E_l} \right) \right)^{-1}
\end{equation}

\textit{D. Equilibrium.}

From the above discussion, we see that the equilibrium Nash bargain price for hospital $k$ is a function of all the other $g-1$ prices, both directly and via the premiums $prem^{G}$ and $prem^{G,k}$, and of consumer choice, given those premiums, of whether to buy insurance and of which hospital to use conditional on buying insurance. Let the vector $\text{price}^*$ be the solution to this system of $g$ equations. Solving the system is complicated by the fact that the $g+1$ profit-maximizing premiums $prem^{G}$ and $prem^{G,j}$ each depend not only on the price vector, but also on $n_{j}^{G}$ and $n_{j}^{G,j}$ for each set of candidate premiums. The profit-maximizing premium, in turn, depends not only on the individual hospital prices, but also on the hospital choice of the marginal consumer. To see this, suppose that the MCO, given a vector of hospital prices, is trying to decide whether it is profitable to cut the premium by enough to attract one more consumer to buy insurance. Whether or not doing so is profitable will depend on which hospital that marginal consumer would choose if he/she bought insurance, which in turn depends on the negotiated price with that hospital.

A proposed vector $\text{price}$ is an equilibrium if the following is true: (i) the set of $g+1$ premiums $prem^{G}$ and $prem^{G,j}$ are each profit-maximizing for the MCO given $\text{price}^*$; (ii) $\text{price}^*$ is a solution to the system of Nash bargaining equations given consumer behavior (i.e., given the choices that consumers make about whether to buy insurance given the premiums and which hospital to use conditional on buying insurance).
D. Mergers.

Now suppose that formerly independent hospital $k$ merges with formerly independent hospital $l$ into a joint hospital system. The Nash bargaining equations of the remaining $g-2$ hospitals will remain unchanged. The bargaining equations for the merged hospitals will depend on whether the merged hospitals continue to bargain independently or they bargain on an “all or nothing” basis.\(^\text{10}\) We consider each of these possibilities in turn.

### i. The Merged Hospitals Continue to Negotiate Independently.

We first consider the case where the merged hospitals continue to negotiate independently. That is, in this sub-section we assume that negotiators for hospitals $k$ and $l$ continue to engage in separate negotiations with the MCO, but that in their negotiations they each internalize the fact that they have a profit stake in the other. An intuitive way to interpret the post-merger payoff to hospitals $k$ and $l$ is to imagine that the pre-merger owner of each hospital remains in charge of negotiating that hospital’s price, but now gets half of the merged entity’s profits.\(^\text{11}\) If a deal is reached with hospital $k$, then the payoff is half of the profits of a two-hospital network. The bargaining equations for this case are as follows.

\[
\begin{align*}
(24a) \max_{\nu_k} & \left[ \left( \frac{n_0^k (\text{price}_k - c) + n_1^k (\text{price}_k - c)}{2} - \frac{n_0^{G-k} (\text{price}_l - c)}{2} \right)^{\alpha} \left( \sum_{j \neq k} n_j^G (\text{prem}^G - \text{price}_j) - \sum_{j \neq k} n_j^{G-k} (\text{prem}^{G-k} - \text{price}_j) \right) \right] \\
(24b) \max_{\nu_l} & \left[ \left( \frac{n_0^l (\text{price}_l - c) + n_1^l (\text{price}_l - c)}{2} - \frac{n_0^{G-k} (\text{price}_k - c)}{2} \right)^{\alpha} \left( \sum_{j \neq l} n_j^G (\text{prem}^G - \text{price}_j) - \sum_{j \neq l} n_j^{G-k} (\text{prem}^{G-k} - \text{price}_j) \right) \right]
\end{align*}
\]

\(^{10}\) The decision of which form the negotiations should take may itself be reflective of the relative bargaining power of the two sides. We ignore the means by which the form of bargaining was chosen and simply lay out the implications of each of the two possibilities.

\(^{11}\) An alternative, equivalent assumption is that the merged entity assigns a negotiator to each negotiation, and then provides those negotiators with incentives such that they act as if they get half of the profits of the merged entity.
Note that the terms in the right-hand sets of parentheses are the same as in (17) above. What changes after the merger is the payoff to each hospital if no deal is reached. In the pre-merger situation, the payoff to hospital \( k \) if no deal was reached was zero. In the post-merger situation, the payoff is half of the profits hospital \( l \). To see the effect of the merger on the equilibrium price, we begin by considering the case where there was no pre-merger competition between \( k \) and \( l \). That is, we consider the case where nobody who would choose \( l \) if \( k \) was not in the network would choose \( k \) if it were in the network, and vice-versa (i.e., \( n_i^G = n_i^{G,k} \) and \( n_k^G = n_k^{G,l} \)). In this case, the terms in the left-hand set of parentheses in each bargaining equation will be the same as in (17) and the merger will have no effect.\(^{12}\)

If there is pre-merger competition between \( k \) and \( l \), then the merger will have an effect. The reason is that if \( n_i^G \neq n_i^{G,k} \) and/or \( n_k^G \neq n_k^{G,l} \), then each hospital’s negotiator internalizes the fact that if they fail to reach a deal, some of the patients that will be lost as a result will use the other merged hospital instead, and so some of those lost profits will be recaptured. This causes each side to bargain more aggressively, and to get a higher equilibrium price. The magnitude of the merger effect is determined by the magnitude of this diversion. This, of course, is a variation on the standard intuition in which diversion is the source of price increases resulting from mergers between substitutes.

As discussed above, the derivation of the \( WTP \) measures depends on the assumption that following the merger the negotiations will proceed on an “all or nothing” basis. This may call into question the appropriateness of using \( WTP \) as a measure of market power for analyses in which the merging firms continue to negotiate separately even post-merger. Nevertheless, we do include \( WTP \) in our independent-bargaining analyses. We do this because \( WTP \), regardless of how

\(^{12}\) The term will be multiplied by a constant of \( \frac{1}{2} \), but this will have no effect on the bargaining outcome.
it is derived, can also be thought of simply as a measure of concentration (since it is based on choice probabilities), and as such can be tested for how well it predicts merger effects.

**ii. The Merged Hospitals Negotiate on an “All or Nothing” Basis.**

The merged entity might instead merge their negotiations and offer their hospitals on an all-or-nothing basis. In this case, the post-merge bargaining equation for the MCO and the merged entity will be:

\[
\max_{\text{price}_k, \text{price}_l} \left[ \left( n_k^G (\text{price}_k - c) + n_l^G (\text{price}_l - c) - 0 \right)^{\alpha} \left( \sum_{j \in G} n_j^G (\text{prem}_j^G - \text{price}_j) - \sum_{j \in G^2} n_j^{G^2} (\text{prem}_j^{G^2} - \text{price}_j) \right) \right]^{1/\alpha}
\]

Under all-or-nothing bargaining, the MCO and the merged entity are bargaining over two prices (\(\text{price}_k\) and \(\text{price}_l\)), but there is only one bargaining equation because both parties care only about the total payment from the MCO to the merged entity if a deal is reached. There are infinitely many combinations of \(\text{price}_k\) and \(\text{price}_l\) to reach any given total payment.

The difference between (25) and (17) above is that in (25), both the merged entity and the MCO are bargaining over two hospitals instead of one. This means that if the negotiations fail, the merged entity will lose two hospital contracts instead of one, and the MCO will suffer a two-hospital hole in its network instead of a one-hospital hole. This doubling of the stakes will not necessarily result in a price increase: if the payoff functions of both the hospitals and the MCO are linear, then the doubling of what the hospitals stand to lose will be exactly offset by the doubling of what the MCO stands to lose, and there will be no price effect. However, if the two merged hospitals are substitutes for each other, then the MCO’s payoff function will be concave and not linear: the loss to the MCO from losing two hospitals will be more than twice as large as the loss from losing one hospital, and this effect will be greater the substitutability between the
two hospitals, and the less substitutable are the other hospitals.\textsuperscript{13} As shown by Chipty & Snyder (1999), a negotiator with a concave payoff function is made worse when its opponent is larger.\textsuperscript{14} The simulations currently included in the paper do not yet include any all-or-nothing bargaining cases. These will be added in the next revision.

IV. Numerical Analysis and Merger Simulation:

A. Generating the Data.

The first step in the numerical analysis is to generate our “data.” In each simulation, we generate data on five hospitals. For each hospital \( j \), we take a random draw on \( U[0,1] \) and call this \( \rho_j \). We then choose two locations for each of the five hospitals, one at the 100\(\rho_j\) percentile of \( U[-6,6]^2 \), and one at the 100\(\rho_j\) percentile of \( N(0,1.2)^2 \). That is, we draw one set of hospital locations from a distribution in which hospitals are equally likely to be located in any location in the support, and another set from a distribution in which hospitals are more likely to be located closer to the center. We also choose a fixed effect for each hospital (\( \eta_j \) in equation (1) above), which is the 100\(\rho_j\) percentile of \( N(0,1.2) \).

In each simulation, we generate data on 100,000 patients. For each patient \( i \), we take a random draw on \( U[0,1] \) and call this \( \mu_i \). We then choose two locations for each patient, one at the 100\(\mu_j\) percentile of \( U[-10,10]^2 \), and one at the 100\(\mu_j\) percentile of \( N(0,36)^2 \). Note that the parameters of

\textsuperscript{13} The reason is that the reduction in consumer valuation of the MCO’s insurance product if one hospital is excluded is mitigated by the fact that the other, competing hospital is included and is a close substitute for at least some consumers. Post-merger if both hospitals are excluded from the network, then consumers who regard the two merging hospitals as roughly equally satisfactory, but who regard the other hospitals as much less satisfactory, will have a larger reduction in their valuation of insurance, and so the MCO will have a larger reduction in its payoff.

\textsuperscript{14} There are other factors that could cause the payoff functions of the hospitals or of the MCO to be concave rather than linear, such as risk aversion. To the extent that this is true, the merger may result in a price increase or a price decrease for reasons that have nothing to do with competition, but simply are a result of the fact that the stakes of the negotiation have increased. However, Sorensen (2003) shows that this effect is modest: hospitals can command slightly higher prices simply by virtue of being larger, but this benefit is much smaller than the benefit from facing less competition.
both the uniform and the normal distributions were chosen so that hospitals are more likely to have relatively central locations compared to the patient population. The distributions of these hospital and patient characteristics are summarized in table 1 below.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital Location</td>
<td>U[-6,6] × U[-6,6], N[0,16] × N[0,16]</td>
</tr>
<tr>
<td>Hospital Fixed Effect</td>
<td>N[0,1.2]</td>
</tr>
<tr>
<td>Patient Location</td>
<td>U[-10,10] × U[-10,10], N[0,36] × N[0,36]</td>
</tr>
</tbody>
</table>

We define consumer preferences as

\[ U_{ij} = -\gamma_1 \text{dist}_{ij} - \gamma_2 \text{dist}^2_{ij} + \eta_j + \epsilon_{ij} \]

where \( \text{dist}_{ij} \) denotes the distance from consumer \( i \) to hospital \( j \), \( \eta_j \) denotes a hospital-specific fixed effect which captures hospital quality, and \( \epsilon_{ij} \) denotes the idiosyncratic component and is assumed to be distributed Type 1 Extreme Value. We use three sets of values for \((\gamma_1, \gamma_2)\) to reflect low, medium, and high travel costs. The values we choose are \((0.3, 0.003)\), \((0.5, 0.005)\), and \((0.7, 0.007)\).

We calibrate the model parameters as follows. We set the bargaining power \( \alpha \) of each hospital to \( \frac{1}{2} \). The parameters \( \lambda_1, \lambda_2, c \), the travel cost parameters, and the parameters of the location distributions and hospital fixed-effect distribution are chosen based on the following criteria.

1) Generate pseudo-\( R^2 \) values that we typically observed in real-world data (0.40 – 0.60).

\[\text{We allowed the location of the hospitals to be determined randomly, rather than as the result of profit-maximizing location, quality investment, and entry/exit decisions. This is partly for simplicity, but it is the case that many hospitals were built many years ago, and so their original locations might no longer be optimal. Moreover, in many states entry decisions are complicated by the existence of “certificate of public need” regulations.}\]
2) The variation in the component of hospital valuation that varies across consumers (locations) explains about twice as much of the observed hospital choices (conditional on insurance take-up) as the variation in hospital valuation that does not vary across consumers (the hospital fixed-effect). This is the rough proportion that we have observed in real-world data.

3) Generate reasonable insurance take-up rates (0.85 - 0.95).

4) Generate reasonable hospital price-cost margins (0.12 - 0.17).

To generate data with the above characteristics, in addition to the aforementioned location and fixed-effect distributions and travel cost parameters, we choose the following parameter values: \( \lambda_1 = 22, \lambda_2 = 0.4, \) and \( c = 4. \)

\[ \] B. Numerical Solution of the Model.

The next step is to solve the model using these generated data. The search algorithm used to solve for the equilibrium vector \( \text{price} \) employs a straightforward Newton-based approach. The only complication in this application is that for a candidate vector \( \text{price} \), a series of searches must be carried out to find a set of optimal premiums for the MCO. The solution algorithm proceeds as follows:

1) Choose a starting price vector \( \text{price} \).

2) Given \( \text{price} \), solve the optimal \( g+1 \) MCO premiums. Since this is a single variable problem, we use a straightforward bisection method.

3) Given the premiums from step (2), evaluate the derivatives of the vector of Nash bargaining problems with respect to own-prices. Update guesses of the \( \text{price} \) using a Newton-
Raphson method. Convergence occurs when the Euclidean norms of the vector of derivatives and the price update are within a tolerance of zero. Here, we use $10^{-10}$.

4) Repeat (2) and (3) to convergence. Convergence occurs when, for a given price vector $\text{price}^*$ and a given premium vector $(\text{prem}^G, \text{prem}^{G_1}, \ldots, \text{prem}^{G_J})$, the Nash bargaining problems in step (3) and the MCO optimization problems in step (2) are simultaneously solved.

Note that we do not re-solve for the optimal premiums for each updated guess of the price vector. We re-solve for the optimal premiums only after the derivatives are solved for prices given a set of premiums. This saves a great deal of computation time. A reasonable and natural alternative would be to simply code the derivatives of the optimal premiums with respect to price and incorporate that into the Newton search. While we may ultimately use this approach, our current approach avoids more the complicated coding associated with this alternative and the bisection method approach to solving the MCO’s problem is very inexpensive and reliable.

As noted above, the inclusion of $\zeta_i$ in the consumer’s insurance valuation ensures that the MCO’s objective function is differentiable in its premiums. By extension, this ensures that the Nash bargaining problems are differentiable in prices. At this time, we do not have a formal proof that the Nash bargaining problems are globally concave in prices, or more generally, that the joint bargaining problem is convex. However, we have tested for convexity using 2000 randomly chosen starting values for the price vector. In this test, the minimums and maximums at the solution for each hospital’s price deviated by no more than $10^{-8}$. Hence, at the present time, we are reasonably sure that the joint Nash bargaining problem has a unique solution.

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true merger effects is greater the larger is $\alpha$.  

22
It is important to note the solving the model does not require that the uncertainty represented by $\zeta_i$ and $\epsilon_{ij}$ be resolved. This is true both before the merger and after, which means that measuring the “true” merger effect does not depend on the uncertainty being resolved. As will be made clear below, the same is not true for the estimated merger effect.

C. Merger Simulations.

The “true” effect of a merger can be simulated by re-solving the model after changing the bargaining according to (24a) and (24b) above. We do 500 merger simulations. As discussed above, each simulation contains six configurations: two sets of hospital/patient locations (one from the uniform distributions and one from the normal distributions), times three sets of travel cost coefficients. Each simulation includes every possible merger (Hospital 1 merging with Hospital 2, Hospital 1 merging with Hospital 3, etc.). Since there are five hospitals, the total number of possible mergers is ten. For each merger, there are two price effects, one for each of the merging firms. So altogether, we simulate $500 \times 2 \times 3 \times 10 = 30,000$ mergers. Since each merger involves two firms, this gives us a total of 60,000 separate sets of prices (with each set containing a pre-merger price, a simulated post-merger price, and a “true” post-merger price).


Given the solution to the Nash bargaining problems in the pre-merger world, $price^*$, the next step is to estimate the relationships between these “true” prices (which correspond to the pre-merger prices than a merger analyst would observe) and the market power variables according to (10) and (16) above. Since the market power measures are based on actual patient choices, this

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17 The WTP measures (unrealistically) constrain rival effects to be zero. The HSHHI measure allows for rival effects to be positive, but there is no economical way to present these given our large number of simulations.
requires that the uncertainty represented by $\zeta_i$ and $\epsilon_{ij}$ be resolved. To do this, we randomly draw values of $\zeta_i$ and $\epsilon_{ij}$ from the Type 1 Extreme Value distribution.\textsuperscript{18} This allows us to determine the set of consumers who would buy insurance from the MCO given the optimal premium that emerges from the solution of the Nash bargaining problem, and which patients will choose which hospitals. We then estimate the conditional logit model, construct the competition measures, and run the price regressions using only the consumers who buy insurance. In this way, we replicate discharge data that a researcher would use in this type of analysis in that real-world discharge data are drawn after the consumers’ insurance decisions have already been made.

\textit{E. Simulation Results.}

The results are summarized in Figures 1-4. The $x$-axis in the figures represents the “diversion” between each hospital and its merger partner. That is, it represents the fraction of those insured patients whose first choice would have been Hospital $k$ (if Hospital $k$ had been in the MCO’s network), who would choose its merger partner Hospital $l$ if Hospital $k$ were omitted.\textsuperscript{19} The $y$-axis represents the quantity (predicted post-merger price – “true” post-merger price)/pre-merger price. That is, the $y$-axis represents the \emph{percentage point difference} between the estimated merger effect and the true one.\textsuperscript{20}

As can be seen in Figure 1 (which compares the true effect to the effect predicted using the “willingness-to-pay per person” simulation method), the predicted effects tend to be below the

\textsuperscript{18} Implicitly, there is an Extreme Value draw associated with not buying insurance as well. So, more precisely, $\zeta_i$ is drawn as a difference of independent Extreme Value random variables.

\textsuperscript{19} We could have done this calculation in such a way as to take account of the fact that the number of people who buy insurance will be different if a hospital is actually omitted from the network, but instead we do it in the way that it would have to be done in a real merger investigation. Specifically, we take the patients in the dataset as the universe, estimate the conditional logit model on that universe of patients, and then see how many patients have Hospital $k$ as their first choice and Hospital $l$ as their second.

\textsuperscript{20} For example, if the predicted merger effect was 10\% and the true effect was 15\%, the $y$-axis value would be -.05.
true ones, and this effect is greater the larger the diversion.\textsuperscript{21} An alternative graphical representation of these same results can be found in Figure 5, which shows a kernel density estimate of the results for all mergers, for those in which diversion $\geq .25$, and for those in which diversion $\geq .5$.

Yet another representation of the same result can be found in Table 2, which shows that the predicted effect is on average 1.9 percentage points lower than the true effect (1.9%), but is 4.2% lower for mergers in which diversion $\geq .25$, and is 6.8% lower for mergers in which diversion $\geq .5$. The probability that the simulation will over-predict the true merger effect by at least five percentage points is correspondingly small: 2.3% for the full sample of mergers, .7% for mergers in which diversion $\geq .25$, and .3% for mergers in which diversion $\geq .5$. In other words, our results suggest that the probability of a substantial Type I error is very small.

Table 2 and the remaining figures contain results for the other three concentration measures: “willingness-to-pay” ($WTP$) as used by Town & Vogt (TV), $WTP$ as used by Capps, Dranove, & Satterthwaite (CDS), and Hospital-Specific HHIs ($HSHHI$). The results are broadly similar across the different concentration measures. They all under-predict the true merger effects on average, and in all of them this tendency is more pronounced the greater the diversion. Furthermore, the standard deviations of the different measures are broadly similar for mergers in which diversion $\geq .25$.\textsuperscript{22} The CDS version of $WTP$ has the greatest tendency to under-predict the true effect (it under-predicts by an average of 9.3 percentage points (9.3%) for mergers in which diversion $\geq .5$), and $WTP_{PP}$ has the least tendency (6.8%).

\textsuperscript{21} Figure 1 should have 60,000 “dots” on it. However, the graphing software that we used only permits 32,000 dots. For this reason, Figure 1 contains 32,000 dots randomly drawn from the 60,000. The same is true for Figures 2-4.

\textsuperscript{22} Note that in Figures 3 and 4, the difference between the predicted effect and the true effect is very close to zero for low levels of diversion, but this is not the case in Figures 1 and 2. The reason is as follows. When diversion is zero, the bargaining model will always return a “true” merger effect of zero. The CDS version of $WTP$ and $HSHHI$ have the property that when diversion is zero, a merger does not change the concentration measure at all, and so the predicted merger effect will be zero, and hence the percentage point difference between the two will also be zero. The TV version of $WTP$ (and the $WTP_{PP}$ measure that is based on it) does not have this property. For this reason, the percentage point difference between the true effect and the predicted effect need not be zero.
Table 3 contains the same information as Table 2, but includes only those merger simulations in which the estimated relationship between price and the concentration measures is positive and has a p-value < .10. It is noteworthy that this involves throwing out quite a lot of observations (for example, in the case of $HSHHI$ it causes the number of observations to fall from 60,000 to 32,540. However, it should be kept in mind that these relationships are each estimated with only five data points (one for each hospital), so it is perhaps not too surprising that a positive and significant relationship is always estimated. As one would expect, throwing out those observations in which the estimated relationship between price and concentration is negative or slightly positive increases the average prediction of the merger effect, and so reduces the degree to which the predicted effects are smaller than the actual effects.

At this stage, we are not certain whether this tendency to under-predict the true merger effects is a robust result, or whether it is an artifact of the particular simulations that we have run so far. We expect that this will be clarified as we run more simulations (see below). One factor that may be contributing to this result is the fact that, at present, there are no hospitals that are already jointly owned before the mergers that we study. This means that for mergers where diversion is high, the post-merger values of the concentration measures are out-of-sample: no hospital in the pre-merger data had values of $WTP$ or $HSHHI$ as high as some post-merger hospitals did. Since the estimation of the relationship between price and the concentration measures is done on pre-merger data, this might bias the estimate, and lead to inaccurate predictions.

VI. Extensions

The primary goal of this paper is to test the accuracy of the merger simulation methodologies based on willingness-to-pay and hospital-specific HHI. However, it should also be possible to
use our bargaining model to simulate specific mergers directly. That is, it should be possible to set up the model in such a way that the locations of the relevant hospitals, populations, geographic barriers, and so on reflect the actual realities of the case in question. The model parameters could then be calibrated to match the observed pre-merger prices, and the merger could be simulated directly. This approach has advantages and disadvantages relative to the approach outlined in this paper, and we leave it as a subject for future research.

VII. Conclusion

In recent years evidence has mounted that some hospital mergers can be expected to result in substantial price increases. As a consequence, researchers have become interested in developing new methods of predicting the effects of hospital mergers. The purpose of this paper is evaluate two of those methods by comparing their predicted post-merger price increases with the “true” price increases for a hypothetical merger using simulated data.

This research can be extended by collecting more results from numerous variations in the environment. The obvious adjustments to our methodology would allow us to test the performance of these merger simulation methodologies allowing some of the non-merging hospitals to be jointly owned, allowing multi-hospital system acquisitions of independent hospitals, and allowing mergers between multi-hospital systems, varying travel costs, the locations of the hospitals and the distribution of the populations, the relative bargaining power of the hospital and the MCOs, and so on. The ultimate goal is to arrive at a situation where it will be possible to identify which version of the price-concentration analysis is most appropriate for a given fact pattern of a merger under consideration. That is, we intend for this work to be of direct use to practitioners of hospital merger analysis (like us).
Appendix

In this appendix, we discuss some of the differences between the TV and CDS version of \( WTP \) and why they are irrelevant for this study. First, TV define \( W_{G\setminus k} \) under two circumstances:

(i) The mean expected welfare of hospital \( k \) is defined on the set \( G\setminus k \)

(ii) The mean expected welfare of hospital \( k \) is defined on the set \( \{G\setminus k, k'\} \), where \( k' \) denotes the best substitute for \( k \) of the currently excluded hospitals.

TV use a switching regression framework to incorporate the uncertainly (from the perspective of the researcher) about which state is generating the data, (i.e., which network is the most relevant in constraining the price of hospital \( k \)). CDS do not observe network exclusions, and so this is irrelevant for their study. In our study, the equilibrium network is always the network of the whole. Hence, the switching regression framework employed by TV is irrelevant for us as well.

Second, TV use DRG weights from Medicare’s Prospective Payment System to weight utilities defining \( W_{G\setminus k} \) over various clinical conditions. The rationale is that more serious conditions should be given more weight in defining consumer valuation of a network. CDS do not use this approach and state in their appendix that TV do not apply the weights correctly. In our study, there is, in effect, only one clinical condition, so the weights are irrelevant.
Third, TV regress log transformations of price and $W_{G&}$ whereas CDS use levels. If using logs, the fitted values from the regressions using the two competition measures would be different. Here, we follow CDS and run our regressions in levels. As such, there is no difference between the fitted values resulting from the regression models using the two measures since the two are linear transformations of one another.

Fourth, TV use price as a dependent variable while CDS use profits. However, since patient volume and, hence, costs are independent of the prices bargained over between hospitals and payers, prices and profits are simple linear transformations of one another. Since we are primarily interested in price effects, we use prices as our dependent variable.
References:


Table 2: Summary Statistics of Percentage Point Deviation
(Estimated – Truth)/Pre-Merger Price

<table>
<thead>
<tr>
<th>Measure</th>
<th>Mean</th>
<th>Stan Dev</th>
<th>F(0.02) - F(-0.02)</th>
<th>F(-0.05)</th>
<th>1 - F(0.05)</th>
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</thead>
<tbody>
<tr>
<td><strong>WTP_PP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>-0.019</td>
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<td>0.548</td>
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<td><strong>HSHHI</strong></td>
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<td>0.058</td>
<td>0.080</td>
<td>0.693</td>
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</table>
Table 3: Summary Statistics of Percentage Point Deviation
(Estimated – Truth)/Pre-Merger Price
Coefficient Estimate > 0 and p-value < 0.10 only

<table>
<thead>
<tr>
<th>Measure</th>
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<th>Stan Dev</th>
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<th>F(-0.05)</th>
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