Countervailing Market Power and Hospital Competition*

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Abstract

While economic theories indicate that market power by downstream firms can potentially counteract market power upstream, antitrust policy is opaque about whether to incorporate countervailing market power in merger analyses. We use detailed national claims data from the healthcare sector to evaluate whether countervailing insurer power does indeed limit hospitals' exercise of market power. We estimate willingness-to-pay models to evaluate hospital market power across analysis areas. We find that countervailing market power is important: a typical hospital merger would raise hospital prices 4.3% at the 25th percentile of insurer concentration but only 0.97% at the 75th percentile of insurer concentration.

Keywords: Mergers, Bargaining, Oligopoly, Health Insurance, Monopsony

JEL Classification: L11, L13, I11, I18

1 Introduction

Academics and policy makers have asserted that an increase in market concentration over the last couple of decades has led to greater markups and higher prices.[1] While the recent literature has largely focused on increases in seller concentration, observers have also raised concerns about buyer concentration.[2] In many markets, seller and buyer market structure (monopoly and monospony power, if you will) interact. Since most industries exhibit a vertical structure with several layers of production before the final product sale, an increase in concentration downstream can exert what Gailbraith famously termed "countervailing power" (Galbraith, 1952). Monopsony power of downstream firms can counteract market power upstream. For example, Walmart might use its leverage to negotiate lower wholesale prices from suppliers in concentrated sectors, and possibly pass on a portion of the savings to consumers.

Understanding the role of countervailing power in affecting prices is particularly relevant for antitrust enforcement. A theoretical literature has shown that, in the presence of countervailing bargaining power, upstream mergers may raise input prices less than they otherwise would (Loertscher and Marx, 2019b) and, in some circumstances, improve welfare (Loertscher and Marx, 2019a). Since the magnitude of the price change from an upstream merger may be affected by countervailing buyer leverage and forecasting the price consequences of a combination is central to merger analysis, the extent of countervailing power should enter into the competitive evaluation of an upstream merger. However, antitrust

[1]Academic articles include Baker (2019); Grullon et al. (2019); Gutiérrez and Philippon (2017); Shapiro (2018); Azar et al. (2017). In the popular press, Francis and Knutson (2015) and Burns et al. (2019) both advance these claims.

[2]Hemphill and Rose (2017) discuss general antitrust concerns with monopsony power and Marinescu and Posner (2019) and Azar et al. (2019) study monopsony power in labor markets.

policy is opaque as to whether and how to incorporate countervailing power in the merger analysis of input products.[3] Influential antitrust academics have also argued that countervailing power should not be given much weight in the competitive analysis, with the justification that more competition is generally good (Baker et al., 2008). In other words, "two wrongs don't make a right."

This paper uses novel and detailed data from the healthcare sector to examine whether downstream monopsony power does indeed limit upstream market power. We focus on hospitals (upstream firms) in their price negotiations with insurers (downstream firms) and study how the impact of hospital competition in affecting prices varies based on insurer market concentration, using a national multi-year dataset of transaction prices.

Healthcare is a particularly important sector for which to consider countervailing power. For the commercially insured population, access to hospitals (which may compete in concentrated markets) is intermediated by insurers. Bilateral negotiations determine the prices that commercial insurers pay hospitals. The bargaining positions of both hospitals and insurers influence negotiated prices, with insurers serving as a potential source of countervailing bargaining power to hospitals and other medical providers. As healthcare accounts for a large (18%) and growing share of GDP, countervailing market power in this sector can have significant welfare consequences.

Our data are from the Health Care Cost Institute (HCCI). They include transaction-level information from millions of hospital claims at thousands of hospitals from three large

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[3]For example, the Federal Trade Commission and Department of Justice's *Horizontal Merger Guidelines* are silent on buyer monopsony power in antitrust market definition, and market definition is a cornerstone of antitrust analysis. In FTC v. Sanford Health et al. (D.N.D. 2017), the district court found that monopsony power should not be considered as part of the market definition process, but the appellate court considered the "dominant buyer" hypothesis (FTC v. Sanford Health et al., 8th Cir. 2019).

insurers over the period 2011-14. We observe the actual prices that insurers paid to hospitals for each inpatient encounter. We estimate the relationship between hospital prices and hospital bargaining leverage and document how this relationship varies across analysis areas, defined by a plan type and focal metropolitan area. We then evaluate whether insurers in concentrated areas leverage countervailing power to lower hospital prices.

Our estimation proceeds in three steps. First, we recover patient preferences by estimating a flexible choice model (Raval et al., 2017) and use our estimates to calculate willingness to pay per person (WTPPP) for each hospital-level observation. Second, separately by analysis area, we regress price on hospital bargaining leverage as measured by WTPPP and cost shifters. The principal output is the constant and WTPPP slope coefficients for each analysis area.[4] Third, we regress these constant and slope WTPPP coefficients on insurer concentration.[5] Together, these regressions allow us to measure how insurer concentration affects hospital prices on average and also whether insurer concentration counterbalances hospital bargaining leverage in its pricing impact.

Findings. We obtain two main findings. First, consistent with the literature, we find that a higher WTPPP leads to higher prices across the majority of analysis areas. Moving WTPPP from its 25th to 75th percentile increases prices by approximately $538 or 4.6% of the sample hospital mean price, at the median level of insurer concentration. We estimate substantial heterogeneity in this effect across our analysis areas. In 83 of the 111 areas, WTPPP is positively associated with prices, with statistical significance at the 5% level in 37 areas. In the remaining 28 areas, the coefficient is negative. It is statistically significant

[4] Bilateral bargaining models (Town and Vistnes, 2001; Capps et al., 2003) motivate this specification.

[5] Following the literature (e.g. Gaynor et al., 2015; Scheffler and Arnold, 2017), we measure insurer concentration using the metropolitan area insurer Herfindahl-Hirschman Index (IHHI).

in 4 of these 28 areas.

Second, we find that an increase in insurer HHI predicts a lower impact of WTPPP on price. That is, when the insurance market structure is more concentrated, hospital systems with higher WTPPP are relatively less able to translate that bargaining leverage into higher prices than hospital systems with lower bargaining leverage. Specifically, moving from the 25th to 75th percentile of WTPPP increases prices 7.1% at the 25th percentile of insurer concentration, but only by 1.5% at the 75th percentile of insurer concentration. Similarly, a typical hypothetical merger—which increases WTPPP 14.4% (Garmon, 2017)—would increase the mean hospital price by 4.3% at the 25th percentile of insurer concentration but only by 0.97% at the 75th percentile of insurer concentration. These findings show the importance and presence of countervailing market power: on average, hospital mergers will have a greater price impact in markets where insurer market structure is less concentrated.

Relation to literature. Our paper primarily relates to two empirical literatures. First, a literature has evaluated the impact of monopsony power in the healthcare sector (Feldman and Greenberg, 1981; Melnick et al., 1992; Sorensen, 2003; Ellison and Snyder, 2010; Moriya et al., 2010; Dafny et al., 2012; McKellar et al., 2014; Scheffler and Arnold, 2017). A common finding is that larger insurers and insurers in more concentrated markets obtain lower hospital prices. We add to this literature by examining how countervailing insurer market power affects the impact of hospital mergers on prices. Countervailing market power concerns the *interaction* of hospital and insurer market power and is distinct from an examination of either hospital or insurer market power.

Second, a different literature has estimated bargaining leverage from hospital choice data and used these estimates to evaluate the price impacts of mergers (Town and Vistnes, 2001; Capps et al., 2003). This literature formalized the idea that WTPPP measures hospital bargaining leverage. Gowrisankaran et al. (2015) and Ho and Lee (2017) developed empirical equilibrium models with oligopolistic insurers and hospitals bargaining over prices. Using these methods, Garmon (2017) finds that the impact of an increase in WTPPP on prices varies across hospital mergers, and a survey article by Gaynor et al. (2015) finds that mergers between hospitals tend to increase prices, but with heterogeneous effects across market settings, hospitals, and insurers.[6] We build on this literature through our use of national data with transaction prices and variation across analysis areas in insurer and hospital bargaining leverage. These national data allow us to examine the impact of WTPPP on prices across many markets, which allows us to understand the impact of countervailing market power. In particular, we assess whether insurers in more concentrated areas prevent hospitals with high WTPPP from exercising their leverage.

2 Empirical Framework

2.1 Theoretical background

Our empirical specification is motivated by a simple bilateral bargaining game between an insurer and a hospital system. This framework is similar to Chipty and Snyder (1999); Capps et al. (2003); Gowrisankaran et al. (2015); Ho and Lee (2017). On-line Appendix A1 describes the relation of our empirical framework to the existing literature.

Consider a market with $m = 1, \dots M$ insurers, $s = 1, \dots, S$ hospital systems, $j = 1, \dots, J$ hospitals, and $i = 1, \dots, I$ individuals. Let $\mathcal{J}_s$ denote the set of hospitals in system s and let $\mathcal{N}_m$ denote insurer m's hospital network.

The game has two stages. In the first stage, insurers and hospital systems negotiate over the transfer payments paid to hospitals. In the second stage, some enrollees become sick and obtain hospital care. The insurer's payoff (at the first stage) from reaching an agreement

[6] Dafny et al. (2012) find that insurance premiums were lower in markets with higher insurance concentration. Trish and Herring (2015) find that insurance premiums are lower in markets with higher insurer concentration and higher in markets with higher hospital market concentration. We do not consider health insurance premiums in this study.

with hospital system s is given by:

$$V_m(s, \mathcal{N}_m) = \pi_m(\mathcal{N}_m) - \pi_m(\mathcal{N}_m \setminus \mathcal{J}_s),$$

where $\pi_m(\mathcal{N}_m)$ is the gross profit that the insurer achieves with all agreements and $\pi_m(\mathcal{N}_m \setminus \mathcal{J}_s)$ is the gross profit the insurer earns in the absence of an agreement with system s.

We assume that when an enrollee needs inpatient hospitalization, she seeks care at the in-network hospital that yields the highest utility. Let q_{jm} be the expected number of insurer m's patients that seek care at each hospital j when in-network (where the expectation is taken at the first stage of the model) and mc_j be hospital j's constant marginal cost. For simplicity, if no agreement is reached between the hospital system and the insurer, the hospital system does not treat any of the insurer's enrollees. Thus, the net value to hospital system s for reaching an agreement with insurer m is $R_{sm} - \sum_{j \in \mathcal{J}_s} mc_j q_{jm}$, where R_{sm} is the negotiated fixed transfer.

The transfer price is determined by "Nash-in-Nash" bargaining. Namely, each bilateral negotiation solves the Nash bargaining solution, embedded inside a Nash equilibrium where the parties to each negotiation treat the outcomes of other negotiations as fixed.[7] The Nash bargaining solution selects the transfer that maximizes the (weighted) product of the surplus from trade relative to the alternative of no trade. We write:

$$R^*_{sm} = \arg\max_r (V_m(s, \mathcal{N}_m) - r)^{1-\theta_{sm}} (r - \sum_{j \in \mathcal{J}_s} mc_j q_{jm})^{\theta_{sm}}$$

where $\theta_{sm} \in [0, 1], \forall s, m$ are the Nash bargaining weights, which capture the relative bargaining power of the two parties. A value of $\theta_{sm} = 0$ gives all the weight to the insurer, while

[7]Horn and Wolinsky (1988) provide an early treatment of this idea. Crawford and Yurukoglu (2012) model Nash-in-Nash empirically and Collard-Wexler et al. (2019) derive its theoretical properties.

$\theta_{sm} = 1$ gives all the bargaining power to the hospital system. Solving this optimization problem and dividing by the expected quantity yields the per-treatment transfer price for each hospital system:

$$p_{sm} = \frac{R^*_{sm}}{\sum_{j \in \mathcal{J}_s} q_{jm}} = (1 - \theta_{sm}) \frac{\sum_{j \in \mathcal{J}_s} mc_j q_{jm}}{\sum_{j \in \mathcal{J}_s} q_{jm}} + \theta_{sm} \frac{V_m(j, \mathcal{N}_m)}{\sum_{j \in \mathcal{J}_s} q_{jm}}. \tag{1}$$

The first term on the right side of (1) is the weighted average marginal cost of the hospital system, multiplied by $1 - \theta_{sm}$. This marginal cost is the threat point (or value without a contract) of the system. When $\theta_{sm} = 0$ (i.e., the insurer has all the bargaining power) the negotiated price will equal this cost: even when the insurer has all the power, the hospital system will not accept less than marginal cost. The second term is the gross insurer surplus from the trade, multiplied by θ_{sm}. The insurer will not agree to pay more than this surplus. Therefore, this is what it gets paid when the hospital system has all the bargaining power. For $\theta \in (0, 1)$, negotiations result in a weighted average of these two extremes, where the weights depend on the relative bargaining power.

To compute $V_m(s, \mathcal{N}_m)$, we would need detailed data on plan enrollment, premiums, and employer contributions, which we do not have. Instead, we follow the literature in proxying for $V_m(s, \mathcal{N}_m)$ with costs and an estimate of the average willingness-to-pay that a given hospital system contributes to a network (Capps et al., 2003). The idea is that, within a market, higher WTPPP and lower cost hospitals increase insurer profits, all else equal. Specifically, we assume:

$$\frac{V_m(s, \mathcal{N}_m)}{\sum_{j \in \mathcal{J}_s} q_{jm}} = \beta^c + \beta^w WTPPP_{sm} + e_{sm}, \tag{2}$$

where $WTPPP_{sm}$ is the expected per-capita consumer surplus that hospital system s contributes to the insurer's network and the residual, e_{sm}, is $i.i.d.$ mean zero.

Substituting (2) into (1), we obtain:

$$p_{sm} = (1 - \theta_{sm}) \frac{\sum_{j \in \mathcal{J}_s} mc_j q_{jm}}{\sum_{j \in \mathcal{J}_s} q_{jm}} + \theta_{sm}\beta^c + \theta_{sm}\beta^w WTPPP_{sm} + \theta_{sm} e_{sm}. \tag{3}$$

Our empirical specification is based on (3). The regressors of interest in (3) are WTPPP and the constant term. We estimate this equation separately for each analysis area because β^c and β^w (which approximate a reduced form of the underlying bargaining relation) may differ across analysis areas due to variation in countervailing market power. For instance, β^w will likely be lower in areas with higher countervailing market power, since insurers will then be able to extract more surplus from high WTPPP hospitals—as they will lose relatively few enrollees from exclusion in these areas—while prices for low WTPPP hospitals will remain relatively similar—since those hospitals were not getting much surplus even without countervailing market power.

2.2 Estimation

Our empirical strategy proceeds in three steps.

Step 1: Estimation of hospital choices. We estimate a hospital choice model using the semi-parametric method of Raval et al. (2017). This approach assumes that patients with similar characteristics have the same choice probabilities for each hospital. We start by grouping admissions together based on them having similar characteristics and calculating choice probabilities for groups that are bigger than a size threshold. We then iteratively remove a characteristic and regroup observations with the smaller set of characteristics, calculating choice probabilities for the new groups that are above the size threshold. We repeat this process until we have assigned choice probabilities for every admission.

We follow Raval et al. (2017) and use a size threshold of 25 and 9 patient characteristics (patient county, ZIP code, major diagnostic category, emergency admit indicator, diagnosis-related group (DRG) type—medical or surgical, DRG weight quartile, DRG, age group, gender), removing the latter characteristics first. Using standard formulas, we obtain WTPPP from our estimates. On-line Appendix A2 provides details.

Step 2: Regressions of price on WTPPP. We estimate an empirical analog of (3):

$$p_{ah} = \alpha_a^c + \alpha_a^w WTPPP_{ah} + \alpha^x x_{ah} + \upsilon_{ah}, \tag{4}$$

where we index observations by analysis area a—which includes the focal metropolitan area and plan type—and hospital/year h. Our measure of plan type indicates whether a claim is from a PPO or a POS plan. $WTPPP_{ah}$ indicates the willingness to pay per person for the hospital system that owns hospital h in analysis area a. While it is now indexed by hospital instead of by system and insurer as in (3), it still indicates the willingness to pay for the entire hospital system.[8]

The vector of hospital cost shifters, x_{ah}, includes year fixed effects, indicators for a hospital's teaching status, for-profit status, and rural location, logarithm of number of beds, full time equivalent residents, and the percent discharges from Medicare and Medicaid. The unobservable is υ_{ah}. We weight specifications by HCCI hospital admissions, and cluster standard errors by hospital system.

We estimate the national distribution of $\hat{\alpha}_a^c$ and $\hat{\alpha}_a^w$ by estimating a separate regression for each analysis area—which amounts to 111 regressions in all. Differences across analysis areas provide variation in insurer concentration and hence in insurer bargaining leverage.

Step 3: Regressions of insurer HHI (IHHI) on analysis area coefficients. In order to measure the impact of insurer concentration, we estimate two separate specifications. The dependent variable in each regression is the estimated coefficients for the 111 different step 2 regressions. Specifically, we regress $\hat{\alpha}_a^c$ and $\hat{\alpha}_a^w$ on IHHI controlling for area characteristics. Our empirical model uses the parameter estimates from (4) as the dependent

[8]We cannot distinguish the different insurers in our data, and hence we do not index WTPPP by insurer m in our empirical work.

variable:

$$\hat{\alpha}_a^c = \gamma^{I,c} IHHI_a + \gamma^{z,c} z_a + \nu_a^c \quad \text{and} \quad \hat{\alpha}_a^w = \gamma^{I,w} IHHI_a + \gamma^{z,w} z_a + \nu_a^w. \tag{5}$$

Our coefficients of interest are $\gamma^{I,c}$ and $\gamma^{I,w}$, which measure the impact of IHHI on the terms estimated in (4). The controls z_a capture factors that may affect prices and bargaining leverage. They include a constant, plan type, hospital utilization (bed days utilized within the analysis area), percent of total population uninsured, and percent of population with income below 200% of the Federal Poverty Level. We pool all data used in the regressions across years.

3 Data and Identification

Our analysis primarily relies on the Health Care Cost Institute commercial health insurance claims database, from 2011 through 2014. This database combines administrative claims from three large, national commercial insurers, Aetna, Humana, and UnitedHealthcare. It includes information for approximately 40 million individuals under 65 years of age enrolled in employer-sponsored health insurance (ESI). The database is unique in its large scope and the fact that it includes "allowed payments" which are the actual transaction-level payments made from the insurer to the provider. These payments are determined through negotiations between the insurers and providers. A limitation of the database is that it does not allow us to infer which claim is from which insurer.

We limit our HCCI analysis sample to individuals with either a POS or PPO plan type. These two plan types account for between 80% and 84% of the ESI enrollment in the HCCI database in each year of the study.[9] The data do not indicate the network for each plan. We

[9]We exclude claims from Health Maintenance Organization (HMO) and Exclusive Provider Organization (EPO) plans. These plans account for a small percentages of the

implicitly infer the network for a given plan type and analysis area based on the presence of sufficient claims. Since we cannot differentiate variation in networks across insurers, this may lead to some measurement error. However, the participating HCCI insurers have broad and similar networks. For our sample in 2014—the year that HCCI first included an out-of-network indicator—fewer than 1% of admissions were for out-of-network hospitals, consistent with other studies on large insurers (Cooper et al., 2020). Thus, we believe that the extent of the measurement error is small.

Additionally, we exclude claims with erroneous or incomplete data, such as missing DRG codes, unclassifiable DRG codes (998 or 999), or allowed payments with negative, zero, or unrealistically low dollar amounts. Low payment amounts are evidence of incomplete claims or coordination of benefit payments and likely do not represent actual prices.

We also limit our claims data to facility claims for inpatient admissions to a general acute care (GAC) hospital. Following previous studies, we exclude claims at GAC hospitals for non-GAC type admissions, admissions for newborns (but not their mothers), and transfers because there is very limited or no choice of hospital for these types of admission (Gowrisankaran et al., 2015). We perform our estimation separately by focal Core-Based Statistical Area (CBSA) but allow our sample of hospitals and patients to extend outside the focal CBSA to capture accurately patient volume and the relevant set of hospital choices. On-Line Appendix A3 provides details on the sample construction by analysis area.

We supplement the HCCI data with multiple other data sources. First, we use Medicare DRG weights to severity adjust hospital prices. Second we use hospital characteristics from the American Hospital Association Annual Survey. We also use these data to construct a measure of hospital utilization as the total inpatient bed days occupied divided by the possible beds days (number of beds $\times$ 365). Third, we use CBSA-level measures of insurer

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total claims resulting in insufficient observations in many analysis areas to conduct analyses comparable to the POS and PPO analyses.

concentration culled from the American Medical Association's (AMA) *Competition in Health Insurance: A Comprehensive Study of U.S. Markets* reports from 2011-2014. Finally, we use socioeconomic measures at the CBSA level from the U.S. Census from the Small Area Health Insurance Estimates Program and the Small Area Income and Poverty Estimates Program. We employ state-level information for hospital observations outside of a metropolitan CBSA.

Hospital Prices. For each hospital and each year, we create a severity-adjusted mean hospital price. This price accounts for the differences in the resources necessary to treat heterogeneous patients. Using patient-level observations, we first calculate a resource-use-adjusted payment by dividing the allowed payment by the corresponding Medicare MS-DRG weight. Then, we regress resource-use-adjusted payments on patient characteristics (age category, gender, age-gender interactions, and length of hospital stay) and a set of hospital dummy variables. We use the patient characteristics coefficient estimates, evaluated at the mean of the population, and the hospital-specific coefficient estimates to calculate the severity-adjusted average price for every hospital. Our approach here is similar to the methods used by Gowrisankaran et al. (2015) and Cooper et al. (2018). We calculate the severity-adjusted mean hospital prices separately by plan type and year.

Insurer Concentration. We measure insurer market structure using the insurer Herfindahl-Hirschman Index (IHHI) reported in the AMA reports. The AMA acquires these data from Decision Resources Group Managed Market Survey. Decision Resources Group collects commercial medical enrollment data from managed care organizations through the Decision Resources Group National Medical and Pharmacy Census. Health insurers are asked for their national, state, and county level enrollment for each plan type and funding type (e.g., fully insured). The AMA data then report IHHI by plan type at the state and CBSA levels. We define a hospital's IHHI based on the CBSA in which it is located, or the state for hospitals not located in a CBSA. We use the mean of IHHI across hospitals in the analysis area as our measure of insurer countervailing market power.

An insurer in HCCI's sample is the largest or second largest PPO plan in all but 3 areas, and is also the largest or second-largest POS plan in the majority of areas. A potential issue is that HCCI data do not include Blue Cross plans, which is the largest group of health insurers nationwide. Despite the exclusion of Blue Cross, we believe that the sizable market shares of the insurers that we have allows us to obtain informative results on monopsony power. Specifically, even in areas where an HCCI insurer is only the second-largest insurer, under many economic theories of competition, it will price similarly to the largest insurer in order to partially exploit the monopsony power present in the market.

Identification. As is common in the literature (see, e.g., Gowrisankaran et al., 2015; Garmon, 2017; Ho and Lee, 2017), we identify the impact of hospital bargaining leverage from cross-sectional IHHI variation in WTPPP within an analysis area. An alternative identification strategy would rely on changes over time in hospital market structure caused by horizontal mergers. Using HCCI data (from earlier years), Cooper et al. (2018) show that pricing models identified from cross-sectional variation yield similar results to those relying on hospital mergers. We also identify the effects of insurer concentration at the CBSA level from cross-sectional variation that we assume to be exogenous. This is a common way to identify the impact of insurer concentration (Moriya et al., 2010; Melnick et al., 2011; Trish and Herring, 2015; Ho and Lee, 2017; Roberts et al., 2017). During our time frame there are an insufficient number of insurer mergers to generate meaningful changes in insurer concentration. Thus, given that our data are national in scope with significant geographic variation in IHHI, we believe this variation is the most credible source available to us.

4 Results

Descriptive statistics of data. Table 1 presents descriptive statistics of our four-year dataset. We analyze POS and PPO plans separately, to allow for the possibility that bargaining leverage and market structure differ across plan type. Our analysis data include 89 POS analysis areas and 22 PPO analysis areas, and account for over 2.25 million unique hospital admissions. Ninety percent of the admissions in our data are among POS plan members.[10]

[10]Some hospitals and some admissions are in multiple analysis areas due to geographic overlap.

Table 1: Analysis sample mean characteristics by plan type

Variable	POS	PPO
Total admissions	2,027,840	223,614
Ages under 18 (%)	4.9	3.9
Ages 18 through 44 (%)	54.9	53.1
Ages 45 through 64 (%)	40.2	42.9
Female (%)	69.8	70.6
DRG weight	1.24 (1.0)	1.25 (1.0)
Hospital-level		
Hospitals per year	2,244 (591)	1,184 (672)
Price ($)	12,535 (5,588)	12,463 (5,629)
Beds	299.1 (246.4)	300.6 (251.8)
Teaching (%)	41.5	43.7
For-profit (%)	16.8	15.6
System affiliation (%)	71.6	73.9
Resident FTEs	61.5 (176.3)	62.5 (181.3)
Medicare discharges (%)	46.3	45.5
Medicaid discharges (%)	19.0	18.6
Rural (%)	1.8	2.5
WTPPP	1.27 (0.2)	1.20 (0.2)
Area-level		
Total analysis areas	89	22
Hospitals per analysis area	181.3 (102.8)	110.9 (65.7)
Insurer HHI	0.482 (0.156)	0.393 (0.127)
Population below 200% of FPL	34.5	33.7

Continued on next page

Table 1 – continued from previous page

Variable	POS	PPO
Uninsured Population	15.4	15.0
Hospital utilization (%)	67.1	66.5

Notes: Mean patient characteristics and mean hospital characteristics are calculated using unique observations in the analysis sample over all years of data by plan type. Mean analysis area characteristics are calculated with using area-level observations averaged over all years by plan type. Standard deviations are shown in parentheses.

Step 1: Hospital choices. Table A1 in On-line Appendix A4 presents summary statistics on the explanatory variables used in our Step 1 estimation.[11] We predicted the largest number of groups using ZIP code and county; the second largest number using major diagnostic category, emergency admittance, and the above two characteristics; and the third largest number using all 9 characteristics.

Table 1 provides summary statistics on WTPPP, the output of Step 1. Although there are many fewer hospitals per analysis area in the PPO sample than in the POS sample, WTPPP is reasonably similar across the samples, at 1.27 and 1.20, respectively. As a point of reference, if each hospital in a market provided the same mean utility to each patient, and a system controlled one-third of the hospitals, the system's WTPPP would be 1.22.[12] Insurer HHI is also similar across the samples, at 0.482 and 0.393, respectively. Both IHHI means are over the regulatory threshold of 0.250 to be considered "highly concentrated" (Federal Trade Commission and Department of Justice, 2010).

Step 2: Impact of WTPPP on prices across analysis areas. We regress WTPPP on severity-adjusted mean hospital prices controlling for hospital cost shifters, as described in Section 2.2. The constant terms from these regressions, $\hat{\alpha}_a^c$, capture the mean price levels in the analysis areas controlling for hospital cost shifters and WTPPP. Across the 89 POS geographic areas, the constant terms range from $-21{,}780$ to 22,870. The range of the 22 PPO constant coefficients is $-10{,}853$ to 24,271. Figure A1 in On-line Appendix A4 graphs the distribution of the constant coefficients (and 95 percent confidence intervals) ordered from lowest to highest.

[11]Our semi-parametric estimator groups similar observations together using different numbers of explanatory variables for different observations based on cell size.

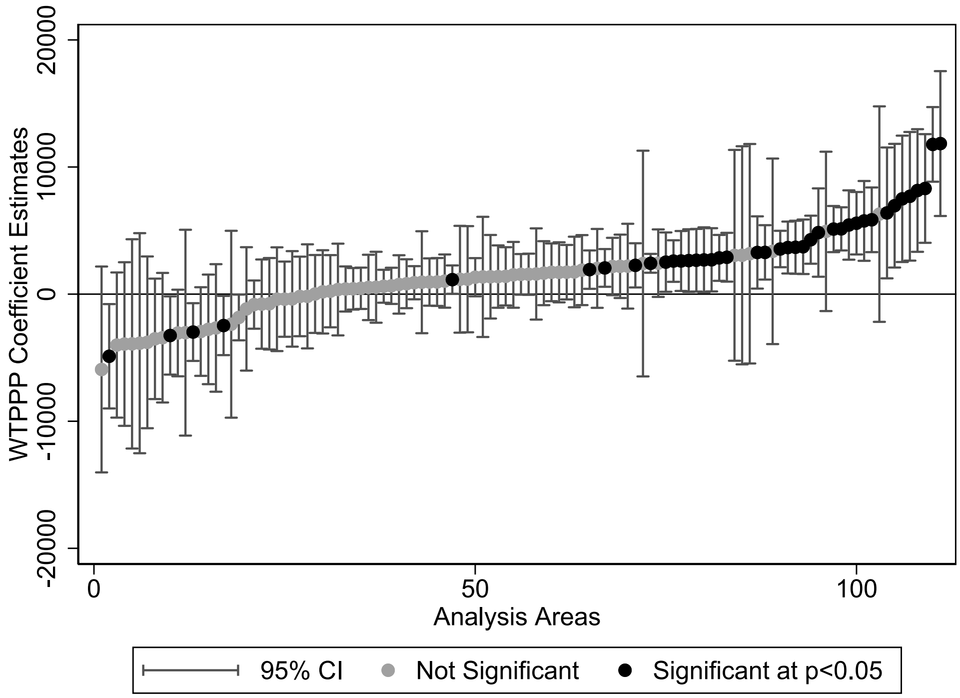
[12]We derive this figure as the WTP for each individual for the system, which is $\ln(3/(3-1))$, divided by the expected probability that the individual seeks treatment at this system, which is 1/3.

The mean and standard deviation of the constant terms over all 111 analysis areas is 9,356 and 6,724, respectively. Among the 20 analysis areas with the same index geographic area for both plan types, the correlation between the constant terms is 0.565. This variability in hospital price levels across areas and plan types is consistent with the significant heterogeneity in private health insurance hospital prices that have been documented elsewhere (Cooper et al., 2018). However, to our knowledge, these estimates are the first that specifically control for hospital bargaining leverage through WTPPP.

The coefficient on WTPPP in these regressions, $\hat{\alpha}_a^w$, captures the impact of changes in WTPPP on hospital prices for that analysis area. Figure 1 shows the distribution of the coefficient estimates, ordered from lowest to highest from each of the regressions, and 95 percent confidence intervals. There is substantial heterogeneity in the impact of WTPPP on hospital prices across analysis areas. Among the POS geographic areas, the WTPPP coefficient estimates range from −5,927 to 11,845, while they range from −4,889 to 6,295 across the PPO geographic areas. The correlation between WTPPP coefficients for analysis areas with the same index geographic area across plan types is 0.619. The mean of the 111 estimates is 1,531 (SD 3,252); 83 of the estimates are positive with a mean of 2,888 (SD 2,449). Of the 83 positive estimates, 37 are statistically significant at the 5 percent level. There are also 4 negative coefficient estimates that are statistically significant. While this may be due simply to random variation, Easterbrook et al. (2019) show that higher WTPPP may lead to lower prices when, for instance, hospitals are complements to insurers.

The majority of the significant coefficients are in the upper third of the distribution of parameter estimates. Since most of the insignificant coefficients have point estimates relatively close to 0, this suggests that the lack of significance in these analysis areas is driven by the coefficient being relatively close to 0 rather than to a differential lack of statistical precision.

Figure 1: Coefficient estimates from Price-WTPPP regressions



Notes: The WTPPP coefficient estimates and their respective 95% confidence intervals are from each of the 111 analysis area regressions, plotted from lowest to highest estimated WTPPP.

Step 3: Impact of IHHI on analysis area coefficients. Table 2 displays results from specifications where we regress the area constant term and WTPPP coefficient estimates on IHHI. The constant term regressions, in columns 1 and 2, indicate $\gamma^{I,c}$, the impact of insurer HHI on prices not considering WTPPP. These results are positive, though not statistically significant.

The WTPPP coefficients, in columns 3 and 4, indicate $\gamma^{I,w}$, the extent to which increases in IHHI are associated with changes in the impact of hospital concentration on hospital prices.[13] These coefficients are negative and statistically significant at the 5% level, are robust to the inclusion of additional controls, to alternative functional forms, and to stratification based on Blue Cross and HCCI insurer shares.[14] The negative coefficients imply that increased insurer concentration diminishes the impact of a hospital's bargaining position on hospital prices. Said somewhat differently, the heterogeneity across markets in the impact of a hospital system's bargaining position on prices is partly explained by insurer market concentration.

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[13]Individually-owned hospitals with very little bargaining leverage will have WTPPP of approximately 1. Combining the coefficients on the constant term and WTPPP, the impact on prices for these hospitals of moving IHHI from 0 to 1 is imprecisely estimated but positive ($17,164 - 12,967 =$ \$4,197 or $20,781 - 12,946 =$ \$7,835).

[14]On-line Appendix A4 reports robustness results.

Table 2: Regressions on insurer HHI of Step 2 coefficients

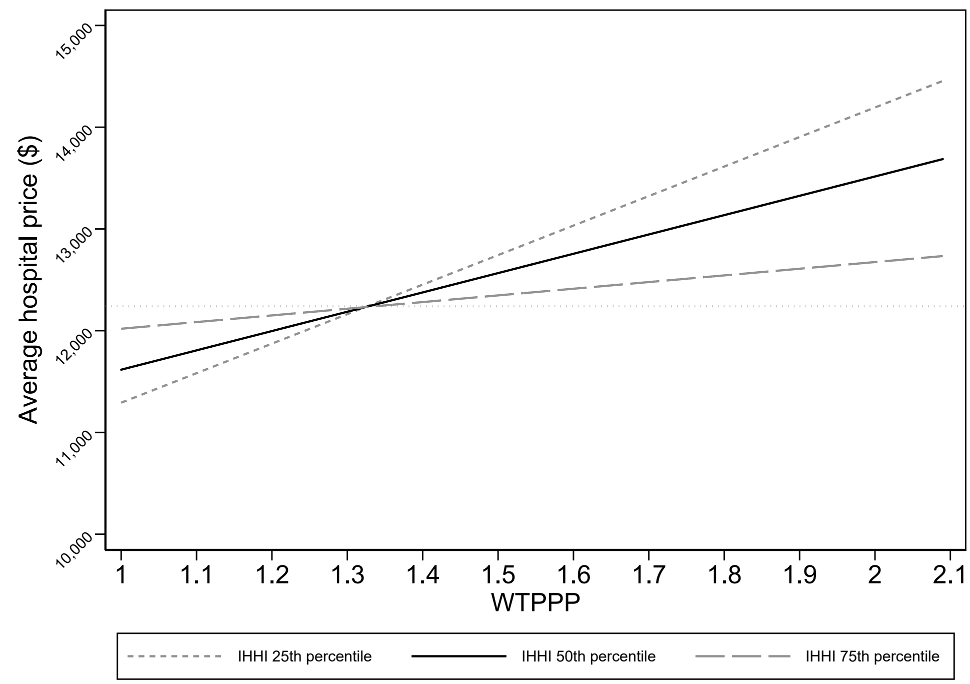
Dependent variable:	Constant terms		WTPPP estimates	
	(1)	(2)	(3)	(4)
Insurer HHI	17,164	20,781	−12,967***	−12,946**
	(12,410)	(14,361)	(4,730)	(5,499)
Below 200% FPL		−115,592***		30,551**
		(19,369)		(14,546)
Uninsured		113,344***		−30,611***
		(20,754)		(11,478)
Hospital Utilization		4,318		1,997
		(21,816)		(9,316)
PPO Indicator	1,954	1,323	−2,155**	−1,894**
	(2,762)	(2,691)	(831)	(897)
Constant	885	19,222	8,066***	802
	(6,257)	(20,708)	(2,316)	(9,622)
N	111	111	111	111
Adjusted R^2	0.012	0.203	0.066	0.102

Notes: Robust standard errors shown in parentheses. ***p-value<0.01, ** p-value<0.05, *p-value<0.1.

We now present graphical evidence to further display our findings of the impact of hospital bargaining leverage and insurer concentration on hospital prices. Figure 2 shows mean hospital prices by WTPPP for the 25th, 50th, and 75th percentiles of IHHI (with the information in table form in Table A5 in On-line Appendix A4). The prices cross at a WTPPP of 1.33 and a corresponding price of \$12,240. This is slightly higher than our sample median WTPPP of 1.22. At the median IHHI level, the mean hospital price would increase by \$538 following WTPPP increasing from its 25th to 75th sample percentile, corresponding to a 4.6% increase in price.

This effect is much higher at the 25th percentile of IHHI. In these markets with low insurer concentration, prices increase by \$822 (7.1%) with this WTPPP increase. Finally, the effect is much smaller at the 75th percentile of IHHI. In these markets with this high insurer concentration, this increase in WTPPP would increases prices by only \$186 (1.5%).

Figure 2: Mean hospital price by WTPPP and insurer HHI

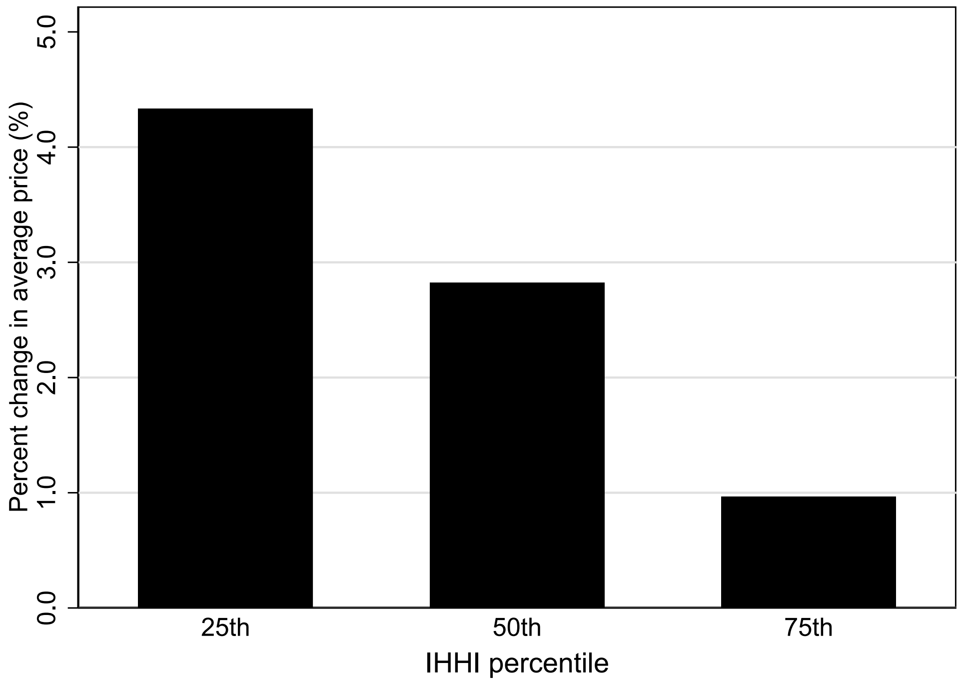


Note: The graph shows the predicted average hospital-level price over the range of WTPPPs for the 25th, 50th, and 75th percentiles of area-level IHHI in our sample. The 25th, 50th, and 75th WTPPP percentiles are 1.08, 1.22, and 1.36 and the 25th, 50th, and 75th IHHI percentiles are 0.3654, 0.4430, 0.5386, respectively.

These numbers suggest that countervailing market power from insurers is potentially important. However, a relevant question is how much this force would constrain the likely impact of price increases for real-world hospital mergers. To address this point, Figure 3 shows the range in percentage changes in expected hospital prices that are likely to occur from a typical hospital merger, but across analysis areas with different levels of countervailing market power. Specifically, we use the mean WTPPP from our sample, 1.26, as the baseline and assume a hypothetical merger increases the WTPPP by 14.4%, the mean percentage change in WTPPP from the 23 hospital mergers reported in Garmon (2017). We then investigate the expected change in prices that would result from this merger across IHHI percentiles of 25, 50, and 75.

We find that this hypothetical merger would increase the mean hospital price by 4.3% if insurer concentration were at the 25th percentile and by 2.8% at the median IHHI. At the 75th percentile IHHI, the merger would increases prices by only 0.97%. These figures do not account for any changes in cost structure that might result from the merger and affect prices. Our results suggest that a policy that only examines the change in WTPPP from a hospital merger, without considering factors such as countervailing market power, would not correctly predict the price impact of the merger.

Figure 3: Change in hospital prices following a hypothetical merger, across IHHI



Note: The graph shows the percent change in hospital price resulting from a merger that increases hospital WTPPP by 14.4%, across the 25th, 50th, and 75th percentiles of area-level IHHI in our sample. These correspond to IHHIs of 0.3654, 0.4430, 0.5386, respectively.

Overall, Figures 2 and 3 show that insurer HHI is an important predictor of the impact of hospital competition on prices. Equivalently, IHHI is an important predictor of whether a hospital merger is likely to raise prices or whether countervailing market power will restrain this potential price increase.

5 Conclusion

Academics and policy makers have been concerned about increases in market concentration, including the interaction of market power by suppliers and buyers. In particular, buyer market power can provide a countervailing force that restricts the ability of concentrated sellers to raise prices (Galbraith, 1952).

We investigate countervailing market power in the hospital sector. This is a particularly important sector for which to understand countervailing market power, given the size of the sector, the levels of concentration on both sides of the market, and the fact that prices are determined by negotiation. We use a novel dataset from HCCI, that is national in scope and has claims information from thousands of hospitals, to understand how the interaction of hospital market power and insurer concentration affects market prices. We find wide variation in the impact of hospital bargaining leverage (which measures hospital market power) on hospital prices. In concentrated insurer markets, hospital bargaining leverage has a much smaller impact on hospital prices than in unconcentrated markets.

In sum, we find evidence in favor of the countervailing market power hypothesis. This conclusion has meaningful policy implications. Specifically, increases in hospital concentration due to mergers may lead to significant price increases in some analysis areas while the same increase in concentration in other areas may have a limited impact on prices. Policymakers may not be able to infer accurately the price impact of a potential merger from its resulting increase in WTPPP without considering characteristics specific to the analysis area such as insurer concentration. This, in turn, suggests that optimal antitrust policy should actively account for insurer countervailing market power when evaluating the impact of hospital mergers.

Our study has several limitations. Most importantly, we do not observe plan premiums. For this reason, we cannot identify the extent to which costs from higher hospital prices are passed on to consumers. Identification derives from variation across analysis areas in insurer market structure. We also cannot distinguish the three insurers from one another in our data. In addition, the HCCI dataset is not the universe of commercial insurers and excludes Blue Cross plans during our sample period. Thus, the results may not generalize to other commercial insurers or other insured populations (e.g. Medicare or Medicaid). Nonetheless, our results add value in that they provide evidence that countervailing market power may be important in hospital markets.

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On-line Appendix

A1 Relation of empirical framework to literature

We estimate empirical specifications that we motivate with a bargaining game. We now compare our framework to the existing literature on hospital bargaining, focusing on Gowrisankaran et al. (2015), or GNT for short.

GNT estimated parameters for one area (Northern Virginia) with four insurers that operate in that area. They observed the insurer for each discharge in their sample and observed data that allowed them to infer coinsurance rates.

We estimate parameters across many analysis areas nationally, with three insurers that operate in these different areas. Our claims data are combined across insurers and hence we do not observe the insurer for each admission in our sample. We also did not use coinsurance data because they were very noisy and coinsurance frequently equaled 0 in our sample.

In a first stage, GNT estimated the price elasticity from the patient choice model, by including as a regressor the individual's out-of-pocket price. Our Step 1 is the analog of GNT's first stage. However, our Step 1 does not include out-of-pocket price as a regressor because of the noisy coinsurance data. Our patient choice model also uses more modern semi-parametric methods than were used by GNT (Raval et al., 2017).

In a second stage, GNT estimated bargaining weights, marginal costs, and a parameter that weights WTP relative to costs in insurers' objective functions, using a GMM framework that matches observed to predicted marginal costs. Our step 2 is the analog of GNT's second stage. We do not recover bargaining weights and these other parameters but instead recover the variation in the relationship between WTPPP and price across markets, which is a function of multiple structural parameters.

We have three principal reasons why we decided not to structurally estimate bargaining weights or separate them from other parameters. First, it would be more difficult here than in GNT to identify the bargaining weights since we lack usable coinsurance data. Second, we could not identify bargaining weights by insurer/hospital pair given that we cannot identify insurer identities. Third, understanding the extent to which countervailing market power across markets increased insurers' relative bargaining power would require estimating a model of insurer competition and we lack data on insurer premiums, shares, and identities that would be necessary to identify such a model. In contrast, Ho and Lee (2017) estimate a model of insurance demand using data on insurance choices and prices for CalPERS enrollees across California and use it in a bargaining framework.

Finally, note that GNT model insurers as valuing enrollee WTP net of costs (in GNT, equation 6, for instance), while we model insurers as valuing profits. GNT did not model competition between insurers and hence they did not directly estimate how profits would change with changes in costs. We assume that insurers compete with each other. Specifically, our profit function π_m captures the fact that if the insurer offers a product with low WTPPP, it will lose enrollees and, through that, have lower profits. Our empirical specification then models insurer surplus as a function of WTPPP and costs. Thus, our model captures the same features as GNT, but with a different functional form. Unlike GNT, we require a model of competition between insurers, because this competition is the source of countervailing market power.

A2 WTPPP Construction

We construct $WTPPP_{ah}$ by estimating patient utility parameters and then simulating changes in values from removing hospital systems. Specifically, denote patient i's utility u_{ij} from choosing hospital j for her inpatient stay as:

$$u_{ij} = \delta_{ij} + \varepsilon_{ij}, \tag{A1}$$

where u_{ij} is a function of the mean utility, δ_{ij}, which depends on interactions of patient and hospital characteristics, including travel costs between patient i and hospital j; and an unobservable ε_{ij}, which is *i.i.d.* and distributed type I extreme value.

We estimate δ_{ij} using the semi-parametric estimator of Raval et al. (2017). The method estimates the probability that each patient i seeks care at hospital j in system s, based on the observable characteristics of the patient and hospital. We denote this probability $prob_{ij}$.

Following Capps et al. (2003), we then calculate $WTPPP_{ah}$ from these probabilities as:

$$WTPPP_{ah} = \frac{-\sum_{i=1}^{I} \log(1 - \sum_{k \in \mathcal{J}_s} prob_{ik})}{\sum_{i=1}^{I} \sum_{k \in \mathcal{J}_s} prob_{ik}}. \tag{A2}$$

where h is the hospital-year for hospital j, the sum is over patients i in that analysis area and year, and $\mathcal{J}_s$ is the set of hospitals in system s.[15] In (A2), the numerator is the sum of the loss in utility from dropping hospital system s across patients while the denominator is the sum of the total expected quantity for hospitals in the system.

A3 Sample Construction by Analysis Area

We perform our estimation of Steps 1 and 2 separately by analysis area. Each analysis area corresponds to an index CBSA and a plan type of POS or PPO, with an average of 1,000 or more admissions per year in the HCCI data. We define analysis areas that are intentionally broad in order to capture accurately patient volume and the relevant set of hospital choices.

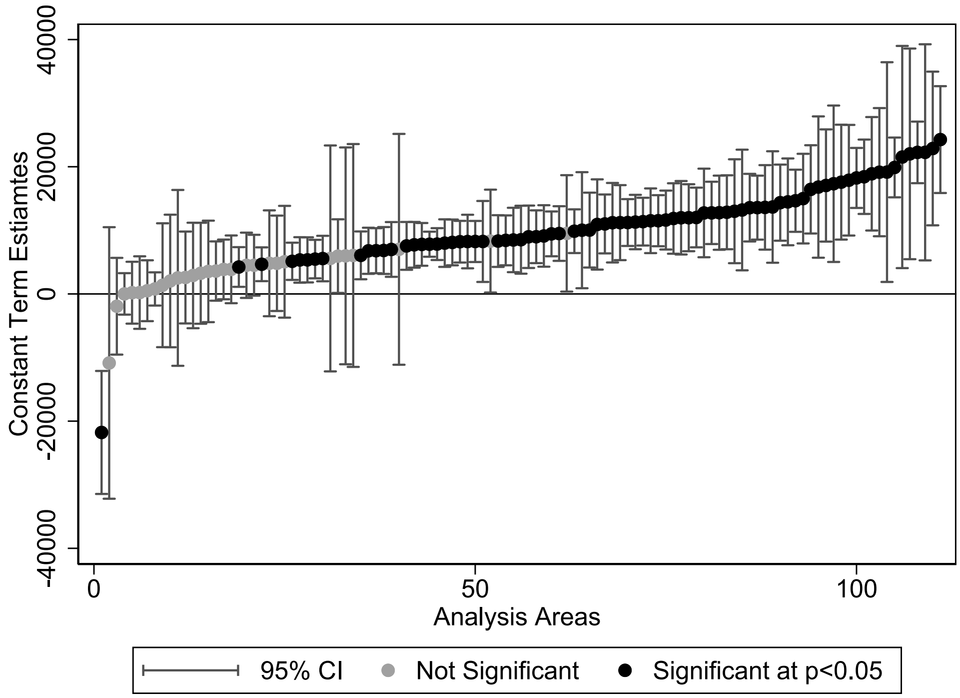
We construct the set of hospitals and patients for each analysis area as follows. We first include all hospitals with at least 25 admissions from the index CBSA and more than 10 beds. We then include all patient admissions with ZIP codes with eligible admissions with admissions to these hospitals that are within 150 miles of the hospital. Finally, we include

[15] The sums in (A2) condition on patients i and hospitals k in the same year and same analysis area as hospital h.

all hospitals with at least 25 admissions from this set of patients and more than 10 beds. With this definition, hospitals in each analysis area may lie inside the index CBSA, outside the index CBSA, and potentially in other CBSAs. Hospitals may also be in multiple analysis areas for the same plan type.

A4 Additional Figures and Tables

Figure A1: Constant term estimates from Price-WTPPP regressions



Notes: The constant term estimates and their respective 95% confidence intervals are from each of the 111 analysis area regressions are plotted from lowest to highest.

Table A1: Summary statistics on explanatory variables for Step 1 estimation

	POS		PPO	
Characteristics	Number of cells	Mean patients per cell	Number of cells	Mean patients per cell
9	23,359	39.3	752	35.1
		(17.9)		(10.6)
8	240	28.5	19	27.9
		(3.4)		(3.9)
7	430	25.2	16	25
		(0.6)		(-)
6	8,772	27.6	315	27.5
		(2.4)		(2.3)
5	7,797	28.8	404	29.0
		(3.8)		(3.4)
4	31,269	30.3	1,075	30.0
		(4.6)		(4.1)
3	19,393	28.8	605	28.6
		(4.0)		(3.8)
2	140,564	60.2	7,148	50.9
		(30.0)		(27.7)
1	14,827	74.9	2,353	92.3
		(84.4)		(131.3)

Notes: The categories used to create cells include: gender, age group, DRG, DRG weight quartile, DRG type, emergency admit indicator, major diagnostic category, ZIP code, county. Cells with 25 or more patients are used to calculate shares used in the WTP calculation. Cells with fewer than 25 patients are returned to sample, one characteristic is removed, and patients are assigned to cells based on the remaining characteristics. The process is repeated until all characteristics are removed. Characteristics are removed in the order noted, gender first, county last. Standard deviations shown in parentheses.

Table A2: Regressions on insurer HHI of Step 2 coefficients from logarithm price on linear WTPPP regression

Dependent variable:	Constant terms		WTPPP estimates	
	(1)	(2)	(3)	(4)
Insurer HHI	1.021	1.242	−0.902***	−0.894**
	(0.865)	(1.000)	(0.327)	(0.378)
Below 200% FPL		−8.764***		2.430**
		(1.353)		(1.026)
Uninsured		7.336***		−1.758**
		(1.372)		(0.719)
Hospital utilization		−0.773		0.667
		(1.499)		(0.623)
PPO Indicator	0.122	0.654	−0.163***	−0.140**
	(0.200)	(0.194)	(0.058)	(0.062)
Constant	8.589***	10.930***	0.624***	−0.400
	(0.433)	(1.418)	(0.159)	(0.646)
N	111	111	111	111
Adjusted R^2	0.003	0.209	0.071	0.127

Notes: Robust standard errors shown in parentheses. ***p-value<0.01, ** p-value<0.05, *p-value<0.1.

Table A3: Regressions on insurer HHI of Step 2 coefficients from logarithm price on logarithm WTPPP regression

Dependent variable:	Constant terms		WTPPP estimates	
	(1)	(2)	(3)	(4)
Insurer HHI	−2.523***	−2.613***	−1.165**	−1.216**
	(0.587)	(0.624)	(0.493)	(0.599)
Below 200% FPL		-3.400**		3.098**
		(1.487)		(1.347)
Uninsured		1.806		−2.098**
		(1.644)		(1.027)
Hospital utilization		−1.693		0.729
		(1.103)		(1.015)
PPO Indicator	−0.304***	0.346***	−0.248**	−0.224**
	(0.093)	(0.103)	(0.085)	(0.095)
Constant	10.21***	12.29**	0.863***	−0.358
	(0.267)	(1.190)	(0.241)	(1.029)
N	111	111	111	111
Adjusted R^2	0.129	0.161	0.067	0.105

Notes: Robust standard errors shown in parentheses. ***p-value<0.01, ** p-value<0.05, *p-value<0.1.

Table A4: Regressions on insurer HHI of Step 2 coefficients with stratification across analysis areas

	Exclude when Blues >50% share	Exclude when Blues largest and >33% share	Include when any HCCI carrier is 1st or 2nd largest	Include when any HCCI carrier is largest
	Dependent variable: Constant terms			
	(1)	(2)	(3)	(4)
Insurer HHI	16,403	16,648	15,499	45,028
	(8,456)	(12,014)	(17,415)	(31,249)
PPO Indicator	2,002	3,953	2,158	9,333
	(2,098)	(2,900)	(3,546)	(6,147)
Constant	1,922	1,557	1,988	−14,324
	(4,263)	(6,212)	(8,815)	(16,744)
N	90	57	79	24
Adjusted R^2	0.015	0.015	-0.003	0.400
	Dependent variable: WTPPP coefficient estimates			
	(5)	(6)	(7)	(8)
Insurer HHI	−10,055*	−7,838	−16,090*	−17,954
	(4,528)	(6,162)	(6,206)	(15,384)
PPO Indicator	−1,815*	−1967	−2,625*	−3,639
	(796)	(1,209)	(1,046)	(2,578)
Constant	6,504**	5,466	9,589**	10,982
	(2,185)	(3,067)	(3,068)	(8,100)
N	90	57	79	24
Adjusted R^2	0.035	0.007	0.075	-0.004

Notes: Exclusion and inclusion criteria based on insurer shares in index analysis areas. Robust standard errors shown in parentheses. ***p-value<0.01, ** p-value<0.05, *p-value<0.1.

Table A5: Mean hospital price by WTPPP values and IHHI percentiles

WTP per person	25th IHHI percentile (3,654)	50th IHHI percentile (4,430)	75th IHHI percentile (5,386)
1.0	$11,293	$11,617	$12,019
1.1	$11,609	$11,824	$12,091
1.2	$11,893	$12,010	$12,155
1.3	$12,178	$12,197	$12,219
1.4	$12,463	$12,383	$12,283
1.5	$12,747	$12,569	$12,348
1.6	$13,000	$12,735	$12,405
1.7	$13,348	$12,962	$12,484
1.8	$13,633	$13,149	$12,548
1.9	$13,918	$13,335	$12,612
2.0	$14,202	$13,521	$12,677
2.1	$14,455	$13,687	$12,734

Notes: The 1st, 25th, 50th, 75th, and 99th WTPPP percentiles are 1.00, 1.08, 1.22, 1.36, and 2.09, respectively.