Multimarket Contact in the Hospital Industry*

Matt Schmitt†
UCLA Anderson

October 2, 2017

Abstract

Hospitals in the U.S. increasingly belong to multihospital systems that operate in numerous geographic markets. A large literature in management and economics suggests that competition between firms may be softened as a result of multimarket contact – i.e., firms competing with one another in multiple markets simultaneously. Exploiting plausibly exogenous variation in multimarket contact generated by out-of-market consolidation, I find that increases in multimarket contact over the 2000-2010 period led to higher hospital prices. These results suggest that continued hospital consolidation may produce higher prices even if that consolidation only minimally affects within-market concentration.

JEL Classifications: I11, L40
Keywords: hospital mergers, multimarket contact

*I thank my PhD advisors, fellow PhD students, and seminar participants at Compass Lexecon, Cornerstone Research, Harvard, Johns Hopkins, NERA, Northwestern, RAND, UCLA, and the University of Pennsylvania for helpful feedback. I especially thank Leemore Dafny, David Dranove, Chris Ody, and Ted Rosenbaum for their detailed comments.

†Email: matthew.schmitt@anderson.ucla.edu

1 Introduction

Over the past several decades, consolidation in the hospital industry has been rapid. Between 2000 and 2010, an average of around 60 general acute care hospital merger and acquisition (M&A) deals occurred each year,[1] with the pace quickening to nearly 100 deals per year between 2011 and 2014.[2] When competing hospitals merge, the combined entity may have greater bargaining leverage in negotiations with insurers, thereby leading to higher prices. Structural merger simulation models often predict substantial price increases resulting from the merger of competing hospitals (e.g., Capps et al. (2003) and Gowrisankaran et al. (2015)), and reduced form studies have found price increases as high as 40 percent (Dafny (2009)). With these effects in mind, antitrust authorities such as the Federal Trade Commission frequently investigate transactions in which the merging hospitals have a strong geographic overlap, attempting to weigh any potential efficiency gains from the transaction against the adverse effects due to lessened competition.

In addition to the traditional anticompetitive concerns generated by mergers between directly competing hospitals, recent hospital consolidation also presents a number of new questions for which existing theory and empirical evidence are more sparse. For instance, many recent hospital mergers do not involve any increases in local provider concentration: in my merger data, 37 percent of hospital mergers between 2000 and 2010 had no hospital referral region (a broad market definition) overlap between target and acquirer, and 13 percent had no overlap even at the state level. Do these types of transactions still have the potential to influence hospital competition, and if so, why? In this paper, I test whether increases in *multimarket contact* led to increases in hospital prices over the 2000-2010 period. As multihospital systems with geographic reach continue to grow – as of 2012, 46 percent of hospitals in my data belong to systems that operate in multiple HRRs and 36 percent belong to systems that operate in multiple states – competition between hospital systems increasingly occurs in several markets simultaneously. An extensive literature in management and economics posits that multimarket contact may soften competition between firms, a conjecture often referred to as the "mutual forbearance" hypothesis.[3]

Using a variety of measures of multimarket contact, the standard approach in the existing

[1]Throughout the paper, I will use the words "merger" and "acquisition" interchangeably. In the vast majority of cases, the merging parties can readily be defined as either "target" or "acquirer."

[2]Sources: American Hospital Association Trendwatch Chartbook 2014, Chart 2.9. Irving Levin Associates, *The Health Care Acquisition Report*, 2014 and 2015. For a review of trends in hospital consolidation during the 1990s, see Cuellar and Gertler (2003).

[3]The mutual forbearance hypothesis dates back to Edwards (1955), but was first formalized by Bernheim and Whinston (1990).

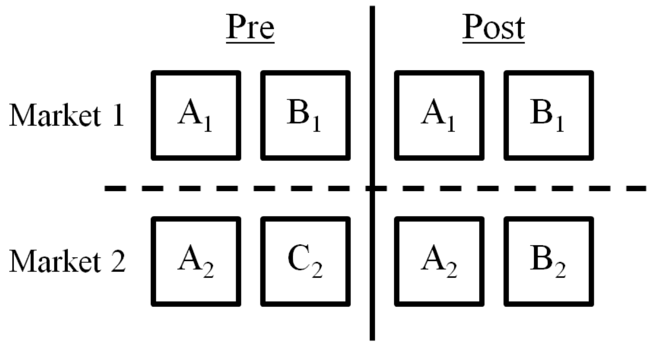

Figure 1: Two Market, Two Hospital Example The left panel (pre) depicts hospital ownership prior to the acquisition of hospital C_2. The right panel (post) depicts hospital ownership after hospital C_2 is acquired by system B. After the acquisition, systems A and B compete with one another in both markets.

empirical literature (e.g., Evans and Kessides (1994)) is to estimate specifications with market fixed effects that exploit within-market variation in multimarket contact over time. One natural identification concern with these specifications is that within-market changes in multimarket contact may be endogenous. To illustrate this concern more precisely, consider the two market, two hospital example depicted in Figure 1.

In the figure, multihospital systems A and B both compete in market 1, but only A competes in market 2. System B then acquires a hospital in market 2, thereby increasing the exposure of both markets to multimarket contact. Using the standard approach, the effect of multimarket contact on prices is estimated by examining price changes in *both* markets. However, the increase in multimarket contact in market 2 occurs at the same time that system B acquires a hospital there, which may cause or be correlated with other factors that affect prices independently of multimarket contact. For instance, management practices at the just-acquired C_2 may change, which can affect pricing. Alternatively, system B may have acquired hospital C_2 because it forecasted strong price growth in market 2. Any such omitted factors will bias the estimates of the effect of multimarket contact on prices.

In an attempt to overcome these concerns, I isolate the variation in multimarket contact coming from situations like market 1 in the example, where the change in multimarket contact is generated by *out-of-market* consolidation. Changes in multimarket contact generated by changes in out-of-market ownership are more plausibly orthogonal to unobserved determinants of in-market prices. For instance, it is less likely that the hospitals in market 1 will undergo simultaneous management changes that affect pricing on top of any effect of multimarket contact. Difference-in-differences models comparing price trends at hospitals experiencing an increase in multimarket contact due to out-of-market M&A (hospitals like A_1 and B_1 in the example) to several different groups of control hospitals reveal a positive and statistically significant effect of multimarket contact on prices. Following an increase in multimarket contact generated by an out-of-market merger, affected hospitals are estimated to experience price increases of 6 to 7 percent. I then examine additional specifications to investigate (a) heterogeneity in price effects and (b) whether alternative theories besides multimarket contact are potentially responsible for the observed price increases.

Prior work on multimarket contact in the hospital industry (Boeker et al. (1997) and Stephan et al. (2003)) examines the impact of multimarket contact on entry and exit patterns of California hospitals between 1980 and 1986. Among other results, the authors find that hospital systems that overlap with competing systems in several markets are less likely to exit any given market, a finding consistent with multimarket contact reducing competitive pressures that may otherwise result in exit. Using national and more recent data, my results corroborate Boeker et al. (1997) and Stephan et al. (2003) by providing direct evidence that multimarket contact may be capable of softening competition and increasing prices.

Recent mergers between national hospital systems have resulted in large increases in multimarket contact.[4] My results suggest that these types of transactions, which may involve only limited changes to within-market concentration – or for which divestitures are required in horizontally overlapping areas in order for the merging firms to receive regulatory approval – may nonetheless lead to higher hospital prices. My paper therefore adds to a burgeoning literature showing that out-of-market hospital mergers can lead to higher prices (Vistnes and Sarafidis (2013), Dafny et al. (2016), and Lewis and Pflum (2016)). Together, these papers highlight the importance of considering factors beyond the local market when evaluating the likely competitive effects of hospital mergers. Beyond the hospital industry, my results suggest that mergers may lead to higher prices via coordinated effects, a finding in line with recent work by Miller and Weinberg (2017) analyzing the MillerCoors joint venture.

The remainder of the paper proceeds as follows. Section 2 provides descriptive statistics about the effects of hospital consolidation on multimarket contact. Section 3 discusses two main obstacles to price coordination in the industry – price observability and intra-system price coordination – and argues that hospitals can plausibly overcome these obstacles. The econometric analysis begins in Section 4, in which I exploit changes in multimarket contact generated by out-of-market mergers in a difference-in-differences framework. In Section 5, I further refine these specifications to distinguish the effects of multimarket contact from other possible mechanisms. Section 6 summarizes and concludes.

[4]For example, Community Health Systems' (135 hospitals) 2013 acquisition of Health Management Associates (71 hospitals).

2 Consolidation in the Hospital Industry

In this section, I first briefly illustrate the effects of recent hospital consolidation on within-market concentration. I then turn to the effects of hospital consolidation on multimarket competition, documenting increases in multimarket contact that are primarily driven by large, national hospital systems.

A long-standing question in studies of hospital competition is how to properly define markets for hospital services (see Dranove and Sfekas (2009) for a nice review of the issues). For the descriptive statistics here I utilize the Dartmouth Atlas' hospital referral region (HRR) which splits the U.S. into 306 distinct areas.[5] The data sources used to generate the statistics shown here are described in the appendix in Section 7.3. Importantly, the data has comprehensive hospital ownership information that I compiled using a combination of (a) the American Hospital Association (AHA) *Annual Survey of Hospitals*, (b) the healthcare M&A market intelligence firm Irving Levin's *Hospital Acquisition Report*, and (c) archived news stories and hospital websites. Comprehensive ownership information is needed to accurately compute measures of multimarket contact.

2.1 Effects on within-market concentration

Figure 2 plots the cumulative distribution function of the Herfindahl index (HHI) across HRRs for the years 2000, 2006, and 2012. Shares are calculated using hospital beds. The vertical lines in the figure mark the HHI thresholds outlined in the DOJ/FTC's 2010 *Horizontal Merger Guidelines*: unconcentrated (below 0.15), moderately concentrated (between 0.15 and 0.25), and highly concentrated (above 0.25). The takeaway from Figure 2 is that hospital concentration has steadily increased over the 2000 to 2012 period. In 2012, only 12% of HRRs were unconcentrated, compared to 22% in 2000. The percentage of highly concentrated HRRs surged over the same period, from 43% in 2000 to 58% in 2012. In a review of the hospital consolidation literature, Gaynor and Town (2012) argue that, on balance, the available evidence suggests that increases in concentration lead to increases in hospital prices. Mergers in concentrated markets in particular have been found to lead to significant price increases, so the high levels of concentration documented in Figure 2 have attracted substantial policy attention.[6]

[5]HRRs are defined by determining where Medicare patients receive major cardiovascular surgery and neurosurgery. Each HRR contains at least one city where patients can receive both types of surgery.

[6]Pear, R. (2014, September 17). F.T.C. Wary of Mergers by Hospitals. *The New York Times*.

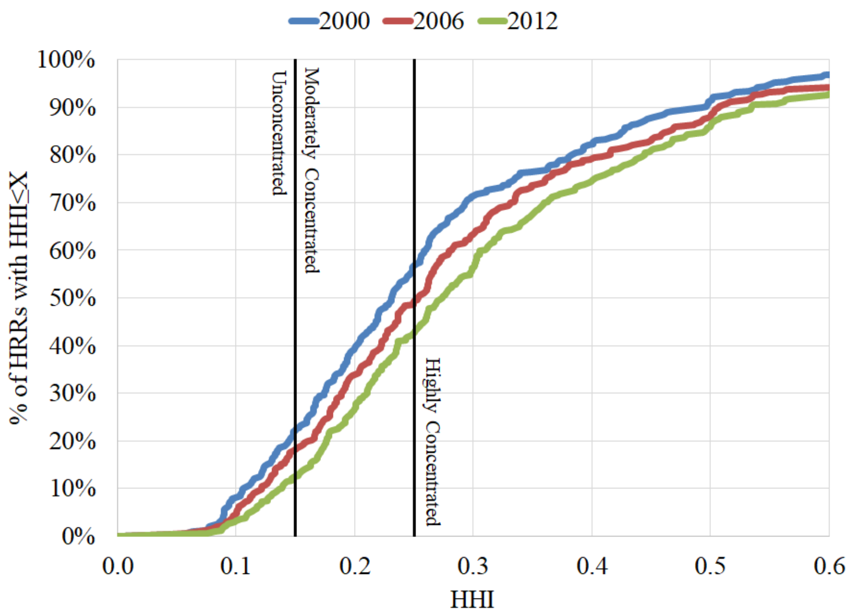

Figure 2: CDF of HHI Across HRRs by Year The figure is censored from the right at HHI=0.6. 3%, 6%, and 7% of HRRs have HHI>0.6 in 2000, 2006, and 2012 (respectively).

2.2 Effects on multimarket contact

Besides the effects of hospital consolidation on within-market concentration as documented above, hospital consolidation has also resulted in increases in multimarket competition, as much recent hospital M&A activity involves large regional and national hospital systems that operate in multiple geographic markets. A common market level measure of multimarket contact in the empirical literature (e.g., Evans and Kessides (1994) and Waldfogel and Wulf (2006)) is the average number of market overlaps per pair of owners in a market. Let mmc_{kmt} denote the number of markets simultaneously served by owners k and m in year t, $\mathcal{F}_{jt}$ denote the set of owners active in market j in year t, and N denote the total number of hospital owners. This measure of multimarket contact, $AvgMMC$, can then be expressed as:

$$AvgMMC_{jt} = \frac{1}{|\mathcal{F}_{jt}|\left(|\mathcal{F}_{jt}|-1\right)/2} \sum_{k=1}^{N-1} \sum_{m=k+1}^{N} \mathbb{1}\left[k, m \in \mathcal{F}_{jt}\right] \cdot \left(mmc_{kmt} - 1\right), \qquad (1)$$

where $\mathbb{1}\left[k, m \in \mathcal{F}_{jt}\right]$ is an indicator that takes a value of one when owners k and m are both present in market j in year t, and zero otherwise. I subtract one from mmc_{kmt} for each pair so that the measure captures the number of *other* markets (besides j) in which owners k and m both compete.

Figure 3 plots the cumulative distribution function of $AvgMMC$ across HRRs for the

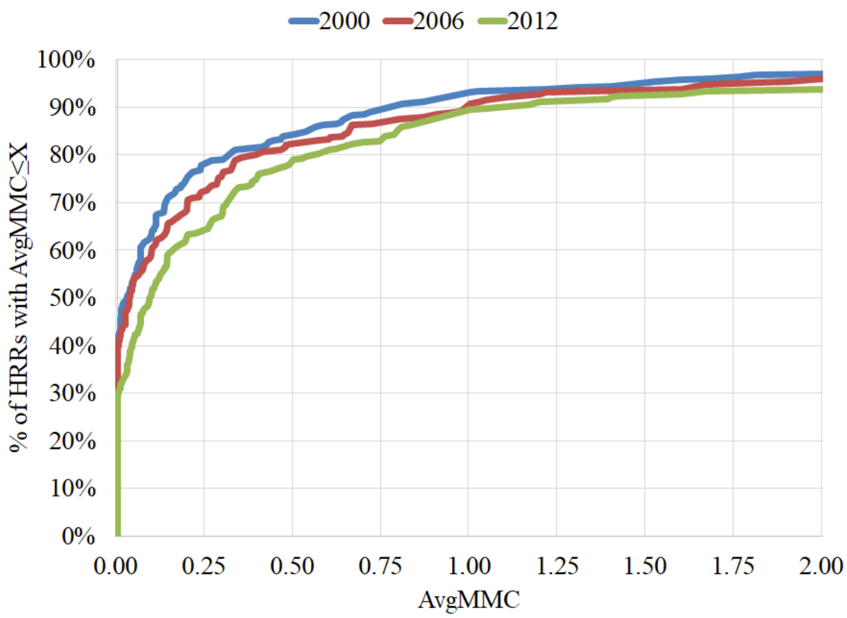

Figure 3: CDF of $AvgMMC$ Across HRRs by Year The figure is censored from the right at $AvgMMC = 2$. 3%, 4%, and 6% of HRRs have $AvgMMC > 2$ in 2000, 2006, and 2012 (respectively).

years 2000, 2006, and 2012. As with HHI, there has been a steady increase in multimarket contact over time. In 2000, over 40% of HRRs had no multimarket contact at all, compared to 29% in 2012. The percentage of HRRs with $AvgMMC$ of at least one – i.e., each pair of owners in an HRR meets one another in at least one other HRR (on average) – also increased from 9% in 2000 to 14% in 2012, a greater than 50% increase. Unlike HHI, there are no rough guidelines for what levels of multimarket contact are likely to indicate feasibility of coordination between firms in a market. It is worth mentioning, however, that compared to an industry like airlines in which firms often compete against one another on hundreds of routes, absolute levels of multimarket contact in the hospital industry are far lower because of the smaller number of markets and the large (though shrinking) number of independent competitors.[7]

2.3 Which systems drive multimarket contact?

To more precisely understand the potential role of multimarket contact in hospital competition, it is helpful to know which hospital systems are responsible for multimarket contact in the industry. In Figure 4, I report the mean of $AvgMMC$ across HRRs after successively

[7]Including independent hospitals, the mean of $AvgMMC$ across HRRs in 2012 was 0.45 and the median was 0.09. Excluding independent hospitals, the mean increases to 1.64 and the median increases to 1.

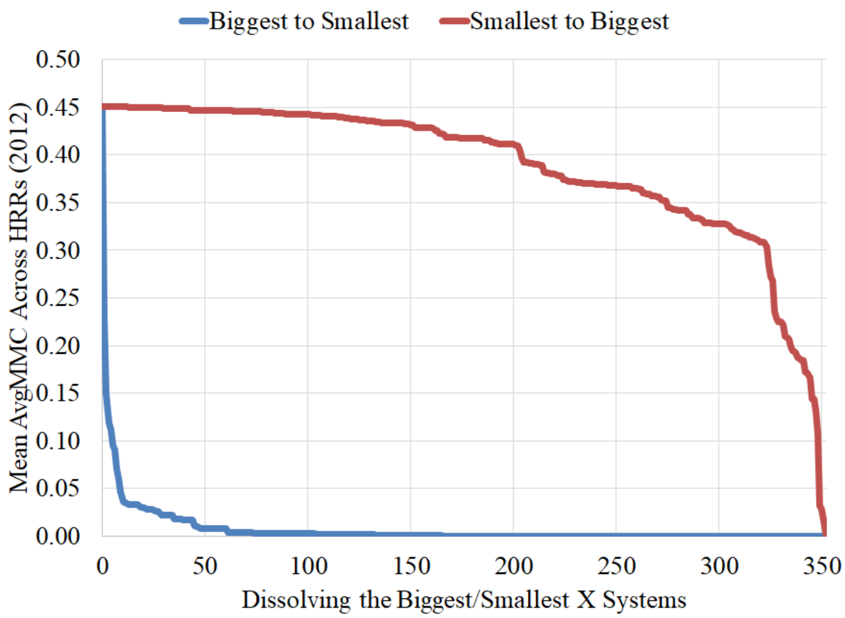

Figure 4: MMC Statistics After Dissolving Hospital Systems, 2012 "Biggest" and "smallest" are in terms of hospitals owned, breaking ties by total hospital beds. Both lines successively replace hospital systems as collections of independent hospitals – going either from biggest to smallest (blue line) or vice versa (red line) – and then recalculate the mean of $AvgMMC$ across HRRs.

"dissolving" hospital systems – i.e., treating the hospitals of multihospital systems as independent. The calculation is performed dissolving systems both from biggest to smallest (blue line) and smallest to biggest (red line), where size is defined in terms of hospitals owned (breaking ties by total hospital beds). First considering the blue line, in 2012, the mean of $AvgMMC$ across HRRs was 0.45. After dissolving just the 10 biggest systems, the mean drops to 0.04. In short, multimarket contact in the industry is largely driven by national hospital systems (e.g., the Hospital Corporation of America). If the hospitals of these systems were independent, there would be very little remaining multimarket contact in the industry.

Turning to the red line, another relevant question is whether multimarket contact is driven entirely by the biggest systems, or if smaller, regional systems also play a meaningful role. While the majority of multimarket contact is driven by competition between the biggest systems – e.g., the mean of $AvgMMC$ across HRRs is still around 0.3 (over 60% of its full value) even after dissolving all but the top 30 systems – the steady decrease as small and medium-sized systems are dissolved indicates that competition between the biggest systems and smaller regional players contributes as well.

3 Multimarket Contact and Obstacles to Collusion

In an early articulation of the mutual forbearance hypothesis, Edwards (1955) writes:

> The interests of great enterprises are likely to touch at many points, and it would be possible for each to mobilize at any one of these points a considerable aggregate of resources. The anticipated gain to such a concern from unmitigated competitive attack upon another large enterprise at one point of contact is likely to be slight as compared with the possible loss from retaliatory action by that enterprise at many other points of contact. There is an awareness that if competition against the large rival goes so far as to be seriously troublesome, the logic of the situation may call for conversion of the warfare into total war. Hence there is an incentive to live and let live, to cultivate a cooperative spirit, and to recognize priorities of interest in the hope of reciprocal recognition.

In short, when competing against one another in many markets, firms may not compete vigorously in any given market for fear of triggering intense competition across all markets. In formal analyses such as Bernheim and Whinston (1990), which look at how the set of collusive equilibria in some game changes when moving from the case of single market competition to competing in multiple markets, this intuition is not complete since increases in multimarket contact affect not only the scope of available punishments for deviations from collusion, but also increase the gains from deviation. Therefore, it is not immediate that additional markets necessarily facilitate collusion. However, under a variety of plausible conditions – differences in the number of firms across markets, differences in growth rates, differences in production costs, stochastic demand fluctuations, concavity of firms' objective functions, etc. – multimarket contact may improve the ability of firms to tacitly collude.[8]

There is a large body of empirical evidence from multiple industries consistent with the mutual forbearance hypothesis.[9] However, the hospital industry is different from many previously studied industries in meaningful ways that may affect the ability of multimarket contact to impact competition. First, the prices negotiated between hospitals and insurers are not publicly observable.[10] Inability to clearly observe the prices of competing hospitals limits the ability of firms to detect deviations from collusive prices and/or follow collusive price leadership strategies. Second, mutual forbearance relies on the ability of firms to coordinate

[8] Notable analyses building on Bernheim and Whinston (1990) include Matsushima (2001) and Kobayashi and Ohta (2012) (imperfect monitoring), Li and Powell (2015) and Sekiguchi (2015) (demand uncertainty), and Spagnolo (1999) (concavity of objective functions).

[9] See Yu and Cannella (2013) for a review of existing evidence. Some studies do fail to find a significant effect of multimarket contact on outcomes, e.g. Waldfogel and Wulf (2006).

[10] Billed charges, which do not reflect the discounts that insurers receive, are much more commonly available.

prices across the markets in which it operates. For instance, if pricing negotiations are delegated to local hospital managers, it must be that those managers consider multimarket contact when acting, and/or gain information from multimarket contact that is relevant to price negotiations. In an extensive review of the multimarket contact literature, Yu and Cannella (2013) emphasize both of these conditions as possible moderators of the collusive potential of multimarket contact. I briefly discuss each condition in turn, arguing that hospitals can plausibly overcome the obstacles.

3.1 Price observability

The rates negotiated between hospitals and insurers are not publicly observable, which all else equal presumably makes sustaining collusion more difficult. That said, there are a number of ways in which hospitals can (and do) attempt to infer the prices received by their competitors, or hire outside consultants to help them. Analysis of aggregated revenue information from Medicare cost report data (the same data source I use in the upcoming empirical analysis), for instance, is one possibility. While any such analysis is unlikely to yield a perfect picture of competitor pricing, it is likely sufficient to give an informative (albeit noisy) signal. Models of hospital price determination at the frontier of the literature such as Gowrisankaran et al. (2015) and Ho and Lee (2017) implicitly assume either that prices are observable or that hospital and insurer beliefs about competitors' rates are correct. In the theoretical literature (Matsushima (2001) and Kobayashi and Ohta (2012)), it is also the case that multimarket contact can still facilitate collusion even when actions are imperfectly observable by increasing the number of signals that firms receive about their rivals.

3.2 Intra-system price coordination

Mutual forbearance relies on the ability of multimarket systems to coordinate prices between hospitals within the system. For large hospital systems, coordinating prices across hospitals within the system is not an uncommon task. For instance, national insurers that serve multistate employers often seek contracts with hospital systems that span several geographic markets. Indeed, one stated motivation for the Trinity Health and Catholic Health East merger was that the expanded geographic reach of the system would enable it to compete for such contracts.[11] Coordination of prices across system members therefore appears to be possible for the large systems that are responsible for the majority of multimarket contact in the industry, and it is likely possible for smaller systems as well.

[11] Evans, M. (2014, June 21). Consolidation creating giant hospital systems. *Modern Healthcare*.

4 Empirical Analysis

4.1 Overview

Ultimately, whether or not multimarket contact affects hospital competition is an empirical question. Early studies of multimarket contact (e.g., Scott (1982)) often used data from a single time period, relying on cross-market variation in multimarket contact to identify its impact. Concerns about correlation between multimarket contact and other unobserved determinants of outcomes across markets motivated fixed effects approaches (e.g., Evans and Kessides (1994)) that continue to characterize recent reduced form analyses of the effects of multimarket contact. These approaches exploit within-market changes in multimarket contact over time to estimate its impact. In Section 7.1 in the appendix, I estimate specifications similar to those commonly utilized in the empirical multimarket contact literature. Consistent with much of the literature, I find evidence of a statistically significant, positive relationship between multimarket contact and prices over the 2000-2010 period. As outlined in the introduction, however, one concern with that analysis is that within-market changes in multimarket contact may be endogenous, even conditional on a rich set of controls. In this section, I instead use out-of-market mergers as a plausibly exogenous source of variation in multimarket contact to estimate difference-in-differences models. Specifically, I examine price trends at hospitals before and after they are "treated" by an increase in multimarket contact that was triggered by an acquisition outside of their market as compared to price trends at a group of control hospitals. Changes in multimarket contact generated by out-of-market M&A are much more likely to be exogenous than changes generated by in-market M&A.

Consider the following illustrative example, depicted in Figure 5. In 2006, Community Health Systems (CHS) acquired Deaconess Hospital, its first hospital in the Oklahoma City, OK metro area. Less than five miles away is St. Anthony Hospital, which is owned by SSM Health Care (SSM). In Mount Vernon, IL, CHS and SSM own hospitals less than two miles apart: Crossroads Community Hospital and Good Samaritan Regional Health Center. CHS' acquisition of Deaconess thereby triggered an increase in multimarket contact between CHS and SSM. One possibility to test whether multimarket contact causes higher hospital prices is to examine prices at all four affected hospitals before and after CHS' acquisition of Deaconess as compared to a set of control hospitals unaffected by multimarket contact; very roughly, this is how prior approaches proceed. However, one might reasonably be concerned that the acquisition of Deaconess is correlated with unobserved determinants of hospital prices.

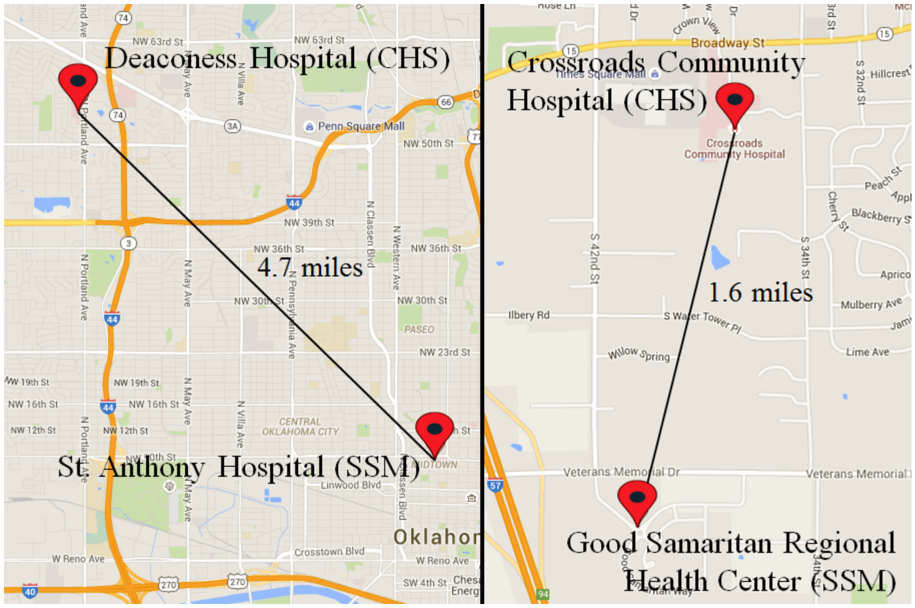

Figure 5: Example of Out-of-Market M&A and Multimarket Contact The left panel is Oklahoma City, OK and the right panel is Mount Vernon, IL. In 2006, Community Health Systems (CHS) acquired Deaconess Hospital in Oklahoma City, less than five miles from SSM Health's (SSM) St. Anthony Hospital. At the same time, both systems owned hospitals within two miles of each other in Mount Vernon, IL. CHS' acquisition of Deaconess therefore triggered an increase in multimarket contact between CHS and SSM.

For instance, if CHS installed new management at Deaconess post-acquisition, any administrative or operational changes may affect pricing for reasons unrelated to (but correlated with) the increase in multimarket contact. Or, as suggested by Lewis and Pflum (2015) and Lewis and Pflum (2016), hospital systems may simply have greater bargaining power, again for reasons unrelated to the increase in multimarket contact. Similar concerns arguably apply to SSM's hospital in the same market, St. Anthony. For instance, CHS' acquisition of Deaconess could have been driven by demand conditions in the broader Oklahoma City market, in which case prices might have changed irrespective of the increase in multimarket contact. Alternatively, CHS' acquisition of Deaconess could have triggered an increase in local concentration (though not in this case since CHS did not own any other Oklahoma City area hospitals), the effects of which may be difficult to separate from any effects owing to the increase in multimarket contact.

In short, there are good reasons to suspect that the merger that triggered an increase in multimarket contact between CHS and SSM may not be exogenous to unobserved determinants of prices at Deaconess Hospital and St. Anthony Hospital. The two hospitals in Mount Vernon, IL – Crossroads Community Hospital and Good Samaritan Regional Health

Center – seem to be a different story, however. Unlike in Oklahoma City, in Mount Vernon there were no clear changes in the local competitive situation at the time CHS acquired Deaconess, and it is unlikely that CHS' acquisition of Deaconess in Oklahoma City was driven by expected price developments nearly 600 miles away in Mount Vernon. Therefore, it is plausible that the increase in multimarket contact triggered by CHS' acquisition is exogenous to unobserved determinants of prices at Crossroads and Good Samaritan. By examining price changes at hospitals that experience increases in multimarket contact but are located away from the merger generating that increase, I can estimate an arguably causal effect of multimarket contact on prices.

4.2 Hospital prices and market definition

Implementing this idea in practice requires a measure of hospital prices as well as a market definition. For price, I use an estimate of the average revenue that a hospital receives per non-Medicare inpatient discharge, net of negotiated discounts with insurers. The same basic measure is used in several studies of hospital prices (e.g., Dafny (2009), Lewis and Pflum (2016)), and is calculated using the Centers for Medicare & Medicaid Services (CMS) Healthcare Cost Report Information System (HCRIS) data.[12] Section 7.3 in the appendix gives the exact line items used to calculate the measure.[13]

Hospitals receive a substantial amount of revenue from government programs such as Medicare and Medicaid. Medicare and Medicaid do not negotiate prices with hospitals as commercial insurers do, so to the extent that multimarket contact affects competition, it should affect prices primarily for commercially insured patients. Ideally, the constructed price measure would therefore only include revenues from patients with commercial insurance. The HCRIS data permits removing Medicare revenues and discharges from the price calculation, but does not contain enough information to eliminate other non-commercial payers such as Medicaid. Hereafter I refer to the HCRIS price measure simply as "price," though in reality it mixes negotiated commercial prices (the true object of interest) with other payment sources, the most prominent of which is Medicaid. The price measure also aggregates over all procedures that the hospital performs, and therefore is sensitive to changes in service mix. As discussed in Section 4.4 below, I include several control variables in the regression analysis to capture aspects of the price formula that do not reflect true price differences but

[12]Medicare-certified hospitals are required to submit comprehensive annual reports to CMS that contain hospital characteristics (e.g., bed counts), utilization information (e.g., inpatient discharges), and financial data (e.g., total charges). These reports are publicly available for download from CMS.

[13]In addition, I adjust prices to 2010 dollars using the consumer price index for all urban consumers.

rather differences in payer and/or service mix.

Prior studies of multimarket contact have often been in industries in which markets can be defined somewhat readily, such as airlines (airport pairs; Evans and Kessides (1994)), radio advertising (FCC-defined radio markets; Waldfogel and Wulf (2006)), and cellular telephone service (standard metropolitan areas; Busse (2000)). In the hospital industry, on the other hand, the question of market definition has been the subject of intense debate both in the academic literature and in the courts. In merger cases, defining the market is an extremely fact-intensive process; doing so exhaustively for every hospital in the data is not feasible. Instead, I use an "own-hospital" market definition that includes in each hospital's market all hospitals within 20 miles in geodesic distance (i.e., as the crow flies).[14] For market definitions with fixed geographic boundaries, a hospital's nearest competitors are not guaranteed to be in the same market, and for that reason I prefer the own-hospital market definition.

4.3 Treatment hospitals

I begin by looking at prices at hospitals like Crossroads and Good Samaritan in Figure 5 (direct effects), rather than other hospitals in the surrounding area (indirect effects).[15] To identify such hospitals in the data ("treatment" hospitals), I start with the set of all acquired hospitals between 2000 and 2010. I then find all hospitals within 20 miles of an acquired hospital (i.e., in the same market). For each pair of owners – the new owner of the acquired hospital and all hospitals within 20 miles – I then check to see if that pair of owners have hospitals within 20 miles of each other elsewhere. If so, I classify those hospitals as treatment hospitals: hospitals that experienced a plausibly exogenous increase in multimarket contact. Both acquired hospitals and hospitals that are within 20 miles of an acquired hospital (i.e., hospitals like Deaconess and St. Anthony in the example) are not classified as treatment hospitals. To further ensure that hospitals in the surrounding area of an acquisition are not included, I require that hospitals classified as treatment hospitals are not in the same hospital referral region as an acquired hospital in the year of treatment. This requirement further restricts the potential pool of treatment hospitals beyond what is imposed by eliminating hospitals within 20 miles of an acquired hospital. Last, I drop all hospitals that were acquired at any point during the period.[16]

[14]The choice of 20 miles is somewhat arbitrary. The results are robust to changes in the assumed radius (see footnote 21).

[15]Results for surrounding hospitals are reported in Section 4.7.

[16]For example, suppose Crossroads had been acquired by CHS the year before. Then, any observed price changes could be the result of the prior acquisition rather than the increase in multimarket contact.

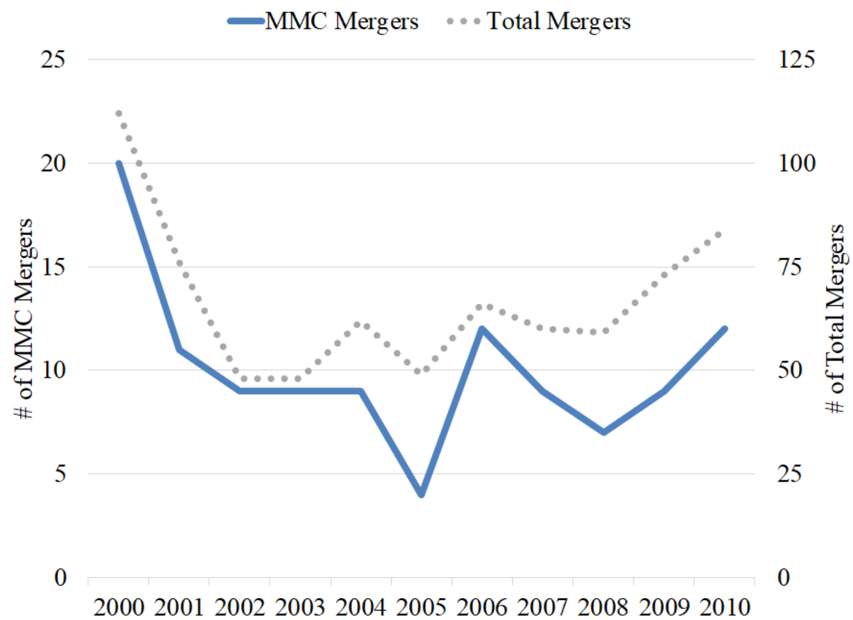

Figure 6: Timing of Mergers Generating Treatment Hospitals The solid line marks mergers that generate treatment hospitals, while the dotted line marks all mergers during the period.

This procedure yields 347 treatment hospitals over the 2000-2010 period which are generated by 111 distinct mergers. Figure 6 plots the timing of these 111 mergers, which closely tracks the overall pattern of mergers during the period. Since treatment hospitals often belong to large and growing systems, about 40% of treatment hospitals are treated more than once during the period. In those cases, I set the year of treatment to be the *first* year in which a hospital was treated. The estimated price effects may therefore also include the effects of subsequent additional increases in multimarket contact, though the results are similar when restricting the sample to hospitals treated only a single time during the period.[17] On average, the mergers triggering increases in multimarket contact involve the acquisition of two hospitals spanning 1.5 hospital referral regions. The acquirer tends to be a large hospital system: the average number of hospitals owned by the acquirer at the time of the merger is 32.8, with a median of 19.

4.4 Regression specification

While I examine mergers in the 2000-2010 period, I utilize data from 1996-2014 in order to have pre and post price information for all treatment hospitals in the sample. Denote the set of all treatment hospitals by $\mathcal{M}$, and let τ_h be the year in which a hospital was first

[17] See Section 7.2 in the appendix for these results.

treated (if ever). See Section 4.5 below for a discussion of control hospitals. I then estimate the following difference-in-differences model:

$$\ln\left(\text{price}_{ht}\right) = \alpha_h + \gamma_t + \lambda \cdot \mathbb{1}\left[t \geq \tau_h, h \in \mathcal{M}\right] + X_{ht}\beta + \varepsilon_{ht}\,, \tag{2}$$

where h is hospital and t is year. The estimating equation includes both hospital fixed effects (α_h) and year fixed effects (γ_t). $\mathbb{1}\left[t \geq \tau_h, h \in \mathcal{M}\right]$ is a post-treatment dummy variable that turns on in the year during which hospital h was treated. The data contains only the year in which each merger occurred, so the year of treatment ($t = \tau_h$) corresponds to a partial year of increased multimarket contact. Since the estimating equation includes hospital fixed effects, the coefficient of interest λ is identified by within-hospital price changes at treatment hospitals compared to control hospitals.

For control variables, I include (log) case mix index, the percentage of inpatient discharges accounted for by Medicaid (% Medicaid), (log) total beds, for-profit status, HHI (based on the own-hospital market definition and computed using bed shares), and a count of other system members. Case mix index, % Medicaid, and beds are included to capture changes in the price measure arising from changes in service and patient mix rather than negotiated commercial prices. For-profit status and HHI are included to control for possible differences in hospital objectives and local competitive forces. Last, the count of other system members is included to control for any independent effects of system growth on prices.

The key identifying assumption when estimating equation (2) is that, absent treatment, treatment hospitals would have exhibited the same price trends as controls. As a suggestive test of this assumption and to see the time path of the effect, I also estimate a more flexible version of equation (2) that includes treatment leads and lags:

$$\ln\left(\text{price}_{ht}\right) = \alpha_h + \gamma_t + \sum_{k=-4}^{4} \lambda_k \cdot \mathbb{1}\left[t = \tau_h + k, h \in \mathcal{M}\right] + X_{ht}\beta + \varepsilon_{ht}\,. \tag{3}$$

Observations more than four years before treatment are included in the $k = -4$ dummy and observations more than four years after treatment are included in the $k = 4$ dummy. In other words, $k = -4$ refers to years at least four years before treatment and $k = 4$ refers to years at least four years after treatment. Due to the inclusion of hospital fixed effects α_h, one of the leads or lags must be dropped. I omit the dummy corresponding to the year before treatment, $t = \tau_h - 1$.

4.5 Control hospitals

When choosing control hospitals, the goal is to find hospitals whose price trends arguably provide the right counterfactual price trends for treatment hospitals (i.e., the price trends treatment hospitals would have followed but for treatment). First, I use "all" other hospitals as controls, excluding hospitals that were acquired at some point during the period, hospitals like St. Anthony in the example, and hospitals within 20 miles of treatment hospitals. The primary benefit of this control group is its simplicity, with the main drawback being that treatment hospitals differ from all other hospitals in several observable ways. Most immediately, treatment hospitals by construction must belong to systems, while the median other hospital is independent. If system hospitals and independent hospitals have systematically different price trends, for instance, then my estimates of λ using this control group will likely be biased. The leads and lags specification (equation (3)) provides a suggestive test of whether this kind of issue is likely to be a problem, but irrespective of those results, one may reasonably question whether all other hospitals are capable of providing the correct counterfactual price trends for treatment hospitals.

Second, I use matching methods from the statistics literature to match treatment hospitals with similar hospitals from the pool of control hospitals.[18] Specifically, I use 1-to-1 optimal Mahalanobis metric matching within propensity score calipers (e.g., see Rubin and Thomas (2000)). For the propensity score, I estimate a logit model using covariates from 1998 – prior to the acquisitions under study – to predict treatment. For the matching, I match exactly on Census division and metro status (i.e., in an MSA) and then choose the match that minimizes the sum of the Mahalanobis distances between the matched pairs. For pairs for which the logit of the propensity score differs by more than 0.2 standard deviations (the recommendation of Austin (2011)), the distance is set to a large value to discourage matches with propensity score differences larger than the caliper. More details on the matching procedure are given in Section 7.4 in the appendix.

Table 1 provides descriptive statistics about treatment hospitals and the hospitals in the two control groups. Compared to treatment hospitals, hospitals in the all control group tend to be smaller in terms of discharges and beds and are less likely to be for-profit or belong to a system. The geographic distributions are also quite different; hospitals in the all control group are more likely to be located in a non-metro area and are more evenly spread across Census divisions. Hospitals in the matched control group are much more similar to treatment hospitals. For Census division and metro status, the differences are reduced to

[18] For a review of the matching literature, see Stuart (2010).

Table 1: **Comparing Treatment and Control Hospitals**

				Abs. Std. Difference	
	Treatment	All Controls	Matched Controls	All Controls	Matched Controls
Hospitals	347	2,603	347	–	–
Price	$7,846	$5,976	$7,483	0.602	0.117
Total Discharges	10,702	5,014	8,956	0.773	0.237
Case Mix Index	1.45	1.22	1.40	0.884	0.220
% Medicaid	0.134	0.129	0.138	0.045	0.041
Beds	244.7	125.3	203.1	0.789	0.275
For-Profit	41.5%	8.5%	24.2%	1.000	0.525
HHI	0.277	0.587	0.369	0.993	0.295
Other System Members	65.0	7.5	28.8	1.468	0.925
Metro (in an MSA)	88.2%	44.9%	88.2%	0.865	0.000
Census Division					
East North Central	12.4%	15.8%	12.4%	0.093	0.000
East South Central	6.6%	8.8%	6.6%	0.076	0.000
Middle Atlantic	5.5%	9.7%	5.5%	0.146	0.000
Mountain	6.1%	8.3%	6.1%	0.084	0.000
New England	0.3%	5.7%	0.3%	0.246	0.000
Pacific	23.3%	8.3%	23.3%	0.498	0.000
South Atlantic	28.0%	12.5%	28.0%	0.440	0.000
West North Central	4.3%	17.7%	4.3%	0.363	0.000
West South Central	13.5%	13.3%	13.5%	0.009	0.000

Notes: All statistics are measured in 1998, or the first year a hospital appears in the data if later than 1998. Price is measured in 2010 dollars. The absolute standardized difference is the absolute value of the difference in means divided by the standard deviation.

zero (by construction). The differences for the remaining covariates shrink as well, though hospitals in the matched control group remain somewhat smaller, less likely to be for-profit, and belong to smaller systems (on average).

4.6 Results

Table 2 presents the coefficient estimates of equation (2) in Panel A and equation (3) in Panel B. For all specifications, standard errors are clustered by hospital and observations are weighted by inpatient discharges. Columns (1) and (3) include only hospital and year fixed effects, while columns (2) and (4) add the additional control variables.

Table 2: Difference-in-Differences MMC Regressions

Panel A: Post Only (Equation (2))

	(1)	(2)	(3)	(4)
	Control Group:			
	All	All	Matched	Matched
Post ($t \geq \tau_h$)	0.064***	0.070***	0.060***	0.065***
	(0.017)	(0.018)	(0.019)	(0.019)
Control variables		✓		✓
Hospitals	2950	2943	694	692
Observations	39,374	39,080	10,645	10,535
R-squared	0.766	0.770	0.708	0.713

Panel B: Leads & Lags (Equation (3))

	(1)	(2)	(3)	(4)
	Control Group:			
	All	All	Matched	Matched
$t \leq \tau_h - 4$	-0.015	-0.016	-0.011	-0.013
	(0.028)	(0.028)	(0.029)	(0.029)
$t = \tau_h - 3$	-0.021	-0.026	-0.012	-0.019
	(0.026)	(0.026)	(0.027)	(0.026)
$t = \tau_h - 2$	0.009	0.006	0.011	0.009
	(0.021)	(0.021)	(0.021)	(0.021)
$t = \tau_h - 1$	0	0	0	0
	–	–	–	–
$t = \tau_h$	0.043*	0.042*	0.044*	0.043*
	(0.024)	(0.024)	(0.025)	(0.025)
$t = \tau_h + 1$	0.069***	0.068***	0.067***	0.067***
	(0.022)	(0.022)	(0.022)	(0.023)
$t = \tau_h + 2$	0.067***	0.068***	0.067***	0.068***
	(0.024)	(0.024)	(0.024)	(0.025)
$t = \tau_h + 3$	0.062***	0.062***	0.062**	0.062**
	(0.024)	(0.024)	(0.025)	(0.025)
$t \geq \tau_h + 4$	0.050**	0.059**	0.050*	0.056**
	(0.025)	(0.026)	(0.027)	(0.027)
Control variables		✓		✓
Hospitals	2,950	2,943	694	692
Observations	39,374	39,080	10,645	10,535
R-squared	0.767	0.770	0.709	0.714

Notes: ***p<0.01, **p<0.05, *p<0.10. Standard errors are clustered by hospital and observations are weighted by inpatient discharges. All specifications include hospital and year fixed effects. The included control variables are (log) Case Mix Index, % Medicaid, (log) Beds, For-Profit status, HHI, and a count of other system members. In Panel B, $t = \tau_h - 1$ (the year before treatment) is the omitted category.

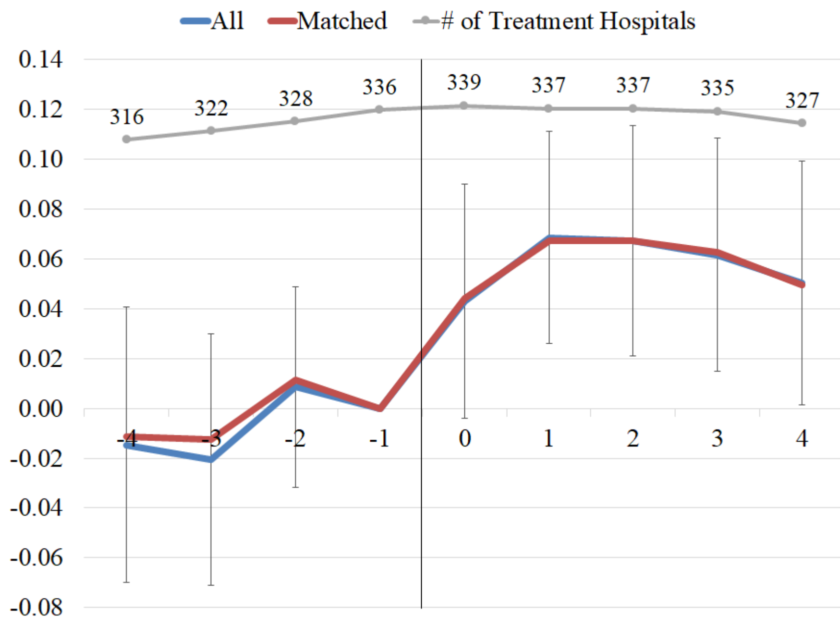

Figure 7: Leads & Lags Results The figure plots the estimated λ_k coefficients from Panel B of Table 2, columns (1) and (3). The year before treatment ($t = \tau_h - 1$) is the omitted category. 95% confidence intervals are plotted for the all controls specification. The number of treatment hospitals entering the regression for each period is plotted above the coefficient estimates. These counts are not equal to the total number of treatment hospitals (347) because of occasionally missing price data.

Figure 7 plots the estimated leads and lags coefficients for the results in columns (1) and (3). Prior to treatment, price growth at treatment hospitals is statistically indistinguishable from price growth at control hospitals.[19] In the year of treatment, on the other hand, prices at treatment hospitals jump up relative to controls and then continue to increase in subsequent years, with some attenuation at the end of the event window.[20] In addition, these results are largely unaffected by the inclusion of the control variables. All told, the results indicate price increases between 6 and 7 percent as a result of treatment.

To evaluate the robustness of these results to changes in the regression specification, I also estimated a battery of additional models that modify various assumptions of the main analysis.[21] Across all such specifications – described briefly in footnote 21 – the estimated

[19]The estimated year fixed effects indicate annualized (CPI-adjusted) price growth at control hospitals of roughly 2%.

[20]It is somewhat surprising that the price effect occurs immediately, especially since hospital-insurer negotiations do not always take place every year. One possibility is that regulatory approval, etc. can take time, such that the formal closing of the deal does not necessarily mark the first date on which competition might be affected.

[21]I estimated the following models. For each model, I report the estimated post coefficient (using the all control group and including the control variables) and stars to denote statistical significance (***p<0.01, **p<0.05, *p<0.10). (1) Clustering standard errors by state (0.070***); (2) Unweighted (0.057***); (3)

effect remains statistically significant and of a similar magnitude.

One caveat to these results is that changes in the cost structure of treatment hospitals may influence pricing, and any such changes would be difficult to disentangle from the effects of multimarket contact. For instance, if expanding hospital systems take on debt in order to grow, it is possible that any corresponding price increases aimed at servicing that debt would bias the estimated post coefficient upward. One way to examine this possibility is to estimate separate effects for treatment hospitals of expanding systems (hospitals like Crossroads in Figure 5) and the remaining treatment hospitals (hospitals like Good Samaritan in Figure 5). The hospitals of non-expanding systems are arguably less likely to experience simultaneous changes in costs that may affect pricing. See Section 5 for these results along with further discussion.[22]

4.7 Indirect effects and effect heterogeneity

To examine indirect effects, I include hospitals within 20 miles of treatment hospitals as a separate treatment group in column (1) of Table 3. If prices are strategic complements, the observed price increases for hospitals directly affected by multimarket contact are expected to be transmitted through to surrounding hospitals.[23] However, the data does not reveal evidence of price increases at surrounding hospitals, as the point estimate is negative and statistically insignificant. A test for equality of the post coefficients rejects the null hypothesis that the effects are equal at the 1% level. While failing to find price effects for surrounding hospitals is somewhat surprising as prices are typically thought to be strategic complements, it is possible that the data is simply too noisy to detect the more nuanced, indirect effect.

I also estimated specifications to attempt to uncover potential heterogeneity in the direct effects. Specifically, if the effect appears to depend on market and transaction features that may affect the feasibility of price coordination. In column (2), I examine heterogeneity by

Dropping the top 10 systems generating treatment hospitals one at a time (minimum 0.061***, maximum 0.076***); (4) 15-mile radius market definition (0.051**); (5) 25-mile radius market definition (0.045***); (6) Restricting the data for treatment hospitals to the four years before, the year of, and the four years after treatment (0.074***).

[22]In addition, in recent work directly examining the effect of mergers on hospital costs (Schmitt (2017)), I did not find evidence of *system-wide* cost changes for hospital systems involved in hospital M&A. While I found that acquired hospitals experience cost reductions post-merger (on average), I did not find evidence of cost changes for existing hospitals of the acquiring system.

[23]In standard models, the transmission of higher prices across hospitals follows from the following mechanism. If the negotiated price at hospital j increases, the value of the insurer's outside option of failing to reach an agreement with hospitals besides j decreases, since absent an agreement some enrollees will be diverted to j (at the higher price). When the value of the insurer's outside option falls, the hospital is able to extract a higher price.

Table 3: Indirect Effects and Effect Heterogeneity

	(1)	(2)	(3)	(4)
Post Direct	0.069***			
	(0.018)			
Post Indirect	-0.017			
	(0.015)			
H_0: effects are equal	0.0001***			
Post*(HHI<.15)		0.028		
		(0.025)		
Post*(.15≤HHI<.25)		0.122***		
		(0.033)		
Post*(HHI≥.25)		0.055**		
		(0.025)		
H_0: effects are equal		0.059*		
Post*(Bed Share<0.2)			0.059*	
			(0.035)	
Post*(0.2≤Bed Share<0.5)			0.082***	
			(0.027)	
Post*(Bed Share≥0.5)			0.061**	
			(0.025)	
H_0: effects are equal			0.806	
Post*(Size Diff≤0)				0.070***
				(0.024)
Post*(Size Diff>0)				0.071***
				(0.022)
H_0: effects are equal				0.974
Hospitals	3,372	2,943	2,943	2,943
Observations	46,099	39,080	39,080	39,080
R-squared	0.765	0.770	0.770	0.770

Notes: ***p<0.01, **p<0.05, *p<0.10. Standard errors are clustered by hospital and observations are weighted by inpatient discharges. All specifications are estimated using the all control group and include hospital fixed effects, year fixed effects, and all control variables ((log) Case Mix Index, % Medicaid, (log) Beds, For-Profit status, HHI, and a count of other system members). For the HHI and Bed Share specifications, HHI and Bed Share are measured in the year of treatment. The bottom of each set of rows reports the p-value of a test of the null hypothesis that there is no heterogeneity – i.e., that all of the effects are equal.

local market concentration. Interestingly, the estimated effect of HHI follows an inverted U-shape, with the largest price effects from multimarket contact for moderately concentrated markets. Equality of the three effects is rejected at the 10% level. One argument consistent with this pattern is that hospitals in unconcentrated markets do not have any ability to raise price while hospitals in highly concentrated markets have already strongly exercised their market power. For hospitals in moderately concentrated markets, on the other hand, there may be more room for the effects of multimarket contact (and coordinated effects more generally) to take hold. That said, this argument is extremely speculative, and the analysis was not designed to rigorously test it – nonetheless, it is an interesting possibility and the results are consistent with it.

In column (3), I explore heterogeneity by the combined bed share of the hospitals experiencing the increase in multimarket contact. The 10th percentile across treatment hospitals is about 20% while the median is about 50%, and I split treatment hospitals into three groups using these thresholds. The point estimates suggest a similar inverted U-shape as with HHI, though the effects are not statistically distinguishable from one another.

In column (4), I examine whether the effect depends on the number of firms in the treatment hospital's market compared to the number of firms in the market(s) triggering the increase in multimarket contact. This specification is motivated by the theoretical analysis of Bernheim and Whinston (1990), which suggests that overlap in a non-competitive market (i.e., with a small number of firms) can help sustain collusion in more competitive markets (i.e., with a large number of firms). Intuitively, slack in the incentive compatibility constraints for sustaining collusion in the non-competitive market can potentially be utilized to sustain collusion in the competitive market. Applied to my analysis, acquisitions in markets with X firms that generate increases in multimarket contact may be more likely to facilitate collusion if the treatment markets affected by the increase in multimarket contact have more than X firms. To investigate this possibility, I calculated the difference between (a) the number of firms in each treatment hospital's market and (b) the average number of firms in the market(s) that triggered the increase in multimarket contact ("Size Diff"). I then estimated separate effects based on whether the difference is positive or not. When the difference is positive, the treated market is more competitive (as measured by the number of firms) than the market(s) triggering the increase in multimarket contact. However, the two estimated effects are extremely similar to one another, thus failing to provide evidence for the specific mechanism of transferring collusive power from less competitive markets to more competitive markets.

That said, it is important to acknowledge the difficulties in constructing strong tests of the mechanisms suggested by theory. First, there can be a substantial degree of correlation between the various measures, which makes isolating any given mechanism difficult. For instance, local market concentration varies across treatment hospitals and is correlated with other measures suggested by theory, such as the Size Diff measure outlined above. This correlation leaves limited independent variation with which to examine specific mechanisms while maintaining statistical precision. Second, a striking feature of the theoretical multimarket contact literature is the large number of circumstances under which multimarket contact may facilitate collusion. One empirical challenge is thus that the operative mechanism may vary across markets in ways that are difficult to predict. In that case, tests of any single mechanism may yield uninformative results. Third, recall that the price measure I use includes non-commercial payers like Medicaid and is sensitive to changes in service mix. Even with controls, these limitations add noise to the price measure, which reduces the power of tests that require examining small slices of the data.

5 Distinguishing Multimarket Contact From Alternative Theories

In this section, I estimate additional specifications that seek to distinguish the effects of multimarket contact from other possible explanations for the main results presented in Section 4.6. To economize on space, the results for these specifications – which are motivated and described in more detail in the following subsections – are all presented in Table 4.

5.1 Differential price trends for treatment hospitals

As discussed in Section 4.5, there is an imbalance between the treatment and control groups with respect to observable hospital characteristics, even after matching. One possible concern with this imbalance is that the types of systems with hospitals that are exposed to multimarket contact – large, for-profit systems – may have systematically different price trends than other hospitals. While the result that prices at treatment hospitals do not appear to be growing faster than controls prior to treatment suggests that this concern may be a non-issue, it can also be examined more directly. In particular, I use the hospitals of systems that generate treatment hospitals – but which are unaffected by multimarket contact – as controls.

For example, Community Health Systems' Martin General Hospital in Williamston, NC was never affected by changes in multimarket contact during the period, while dozens of other Community Health Systems hospitals were; hospitals like Martin General are therefore natural control hospitals to use in estimation. Intuitively, identification with this control group is driven by differences in price trends between hospitals in the *same system* – e.g., if Community Health Systems hospitals exposed to multimarket contact exhibit faster price growth post-treatment than Community Health Systems hospitals that were not exposed to multimarket contact. While hospitals in this "same-system" control group do share system membership with treatment hospitals, and are therefore likely similar in terms of unobservable factors influencing prices such as management practices, they do tend to be smaller and more rural. In other words, it is not as if treatment within system is random. Nonetheless, utilizing this control group should take care of any system-wide factors unrelated to multimarket contact that may affect prices.[24]

Results using the same-system control group are shown in column (3) of Table 4. In the first set of rows ("Main results"), columns (1) and (2) are copied from Panel A of Table 2. Column (3) gives the result using the same-system control group, indicating a somewhat smaller though still statistically significant effect of multimarket contact on prices. The remaining sets of rows, which correspond to further refinements of the regression specification, are explained in more detail below.

5.2 Contemporaneous changes in input costs and/or service mix

Medicare pays hospitals according to a formula that does not depend on multimarket contact, but does depend on factors like area wage costs and case complexity. If the observed price increases at treatment hospitals are due to coincident changes in things like wage costs or overall service mix, it might be expected that treatment would also affect the average revenue that treatment hospitals receive from Medicare patients ("Medicare prices"). If there is no effect on Medicare prices, on the other hand, it is more likely that the observed effects for non-Medicare prices are truly capturing changes in negotiated prices due to multimarket contact rather than simultaneous changes in other factors that influence the price measure. The second set of rows in Table 4 shows the results from estimating equation (2) but with the log of Medicare price as the dependent variable. I find no evidence of changes in Medicare prices: for all three control groups, the point estimate is close to zero and statistically insignificant.

[24]Another way to implement this idea is to add system by year fixed effects to the regression specification. Doing so yields results similar to those reported in Table 4 in all cases. The estimated post coefficients, with stars to denote statistical significance (***p<0.01, **p<0.05, *p<0.10), are given by: (1) non-Medicare price (0.060***), (2) Medicare price (-0.003), (3) Active (0.075**) and Passive (0.047*), (4) In-State (0.060**) and Out-of-State (0.059**).

5.3 Other cross-market mechanisms

Several other recent papers provide alternative mechanisms besides multimarket contact through which hospital competition can potentially be linked across geographic markets. Lewis and Pflum (2016) (LP) find that prices of hospitals acquired by out-of-market systems increase by 17 percent post-acquisition, and argue that the observed price increases may be due to systems having greater bargaining power, irrespective of the local competitive environment. While I exclude hospitals that were acquired at any point during the period, it is possible that LP's bargaining power channel also applies to existing members of the acquiring system, even away from the area of the acquisition.

Dafny et al. (2016) (DHL) provide mechanisms through which the presence of common customers (e.g., employers who draw employees from multiple hospital markets) and/or common insurers across markets can generate cross-market merger effects.[25] For example, an employer located in a city center choosing a single insurance plan for its employees may simultaneously value hospitals in both the northern and southern suburbs of the city, and therefore the merger of even faraway hospitals could potentially generate price effects. Examining hospitals that belong to systems involved in mergers but are not located in horizontally overlapping areas, DHL find that hospitals in the same state as acquired hospitals experience 7 to 10 percent price increases post-merger while hospitals out-of-state do not. These empirical results provide support for the common customer and common insurer mechanisms, which are both likely to be stronger within states than across them.

Since my identification strategy relies on examination of price trends at existing system members away from the area of the acquisition, it is possible that LP and DHL's mechanisms are present in my sample. That said, it is possible to further refine the regression specification in an effort to more precisely isolate multimarket contact from LP and DHL's mechanisms.

The first piece of evidence that LP and DHL's mechanisms are unlikely to be fully responsible for the effects I observe is the results utilizing the same-system control group. There, counterfactual price trends for hospitals affected by multimarket contact are estimated using hospitals belonging to the *same systems* (but which are not affected by multimarket contact). If the acquisitions triggering increases in multimarket contact only affect prices via LP and DHL's mechanisms, it is likely that the "control" hospitals in that specification will be affected as well. Yet, the estimated price effect remains positive and statistically

[25] Vistnes and Sarafidis (2013) also demonstrate mechanisms through which mergers can impact competition even without direct patient substitution. While for convenience I refer to "DHL's mechanisms" in the subsequent discussion, I fully acknowledge the contribution of Vistnes and Sarafidis (2013) as well.

Table 4: Distinguishing Multimarket Contact from Alternative Theories

	(1)	(2)	(3)
		Control Group:	
	All	Matched	Same-System
Main results (non-Medicare price)			
Post ($t \geq \tau_h$)	0.070***	0.065***	0.054**
	(0.018)	(0.019)	(0.022)
Medicare price falsification test			
Post	-0.000	0.005	0.002
	(0.006)	(0.006)	(0.006)
Active and passive effects			
Post Active	0.084***	0.079***	0.068**
	(0.029)	(0.029)	(0.031)
Post Passive	0.058***	0.052**	0.041*
	(0.019)	(0.020)	(0.022)
H_0: effects are equal	0.415	0.396	0.392
In-state and out-of-state effects			
Post In-State	0.071***	0.066***	0.055**
	(0.019)	(0.021)	(0.023)
Post Out-of-State	0.068**	0.062*	0.052
	(0.033)	(0.034)	(0.036)
H_0: effects are equal	0.925	0.904	0.933

Notes: ***p<0.01, **p<0.05, *p<0.10. Standard errors are clustered by hospital and observations are weighted by inpatient discharges. All specifications include hospital fixed effects, year fixed effects, and all control variables ((log) Case Mix Index, % Medicaid, (log) Beds, For-Profit status, HHI, and a count of other system members). The bottom of the third (fourth) set of rows reports the p-value of a test of the null hypothesis that the active/passive (in-state/out-of-state) effects are equal.

significant, albeit somewhat smaller in magnitude.

Second, in the main difference-in-differences analysis, I do not distinguish between the hospitals of the system that made the acquisition that triggered the increase in multimarket contact ("active" hospitals like Crossroads in Figure 5) and hospitals without any change to the system ("passive" hospitals like Good Samaritan in Figure 5). LP and DHL's mechanisms may predict price effects for active hospitals – e.g., if an acquisition increases bargaining power system-wide – but not for passive hospitals, at least directly. Prices at passive hospitals may be affected through strategic complementarity, though recall that I do not find evidence of price increases at other surrounding hospitals (Section 4.7). The third set of rows in

Table 4 shows the results from a specification splitting the treatment group by whether the increase in multimarket contact was generated by an acquisition of the treatment hospital's own system (i.e., whether the treatment hospital is active or passive). The point estimates for both active and passive treatment hospitals are positive and statistically significant (at the 10% level or lower) for all three control groups. Interestingly, while the differences are not statistically significant, the point estimates for active hospitals are larger than the estimates for passive hospitals, which is consistent with LP and DHL's mechanisms also being present (though likely unable to fully explain the results).

Third, in the main difference-in-differences analysis, the variation in multimarket contact generated by out-of-market M&A comes both from in-state (but out-of-market) and out-of-state M&A. The effects of treatment from in-state acquisitions are more likely than out-of-state acquisitions to involve simultaneous effects from LP and DHL's mechanisms. Any increases in bargaining power may dampen with distance and the common customer/insurer channels are also less prevalent across states. The fourth set of rows in Table 4 shows the results from a specification splitting the treatment group by whether the increase in multimarket contact was generated by an in-state or out-of-state acquisition. The point estimates for the in-state and out-of-state treatment groups are positive, of similar magnitude, and mostly statistically significant. Identification with the same-system control group is particularly demanding, so it is unsurprising that at some point statistical significance goes away. As with the active/passive analysis, the estimated in-state effects are larger than – though not statistically distinguishable from – the out-of-state effects, which is again consistent with LP and DHL's mechanisms also being present to some degree.

To summarize, the additional specifications examined in this section suggest that current alternative theories through which out-of-market mergers may influence competition are unlikely to fully (or even mostly) explain the observed price increases following increases in multimarket contact. In other words, on balance the results seem to indicate that multimarket contact has a causal impact on prices, as opposed to spuriously capturing the impact of other mechanisms that have also been found to affect prices.

6 Conclusion

In this paper, I find evidence that multimarket contact leads to higher hospital prices. To address the potential endogeneity of within-market changes in multimarket contact, I estimate difference-in-differences models that isolate variation in multimarket contact generated by out-of-market consolidation. I find a positive and statistically significant effect of multimarket contact on prices, and the results are robust to a variety of modifications to the regression analysis.

Importantly, my estimates are limited to the prices paid to hospitals by private insurers. How much consumers are ultimately affected depends on the pass-through of insurer costs to premiums and/or other elements of plan design (e.g., coinsurance rates). Recent structural work by Ho and Lee (2017) simultaneously models both hospital price determination and insurance premium setting, which allows for predictions of pass-through, as well as giving insights about how pass-through may depend on important market characteristics such as insurer market structure. To my knowledge, there are no reduced form estimates of pass-through in the industry available. Such estimates would be useful to provide a more complete interpretation of the effects of forces that may impact hospital-insurer bargaining.

Beyond the 2000-2010 study period analyzed here, there have been several mergers between national hospital systems that have further increased the extent of multimarket contact in the industry.[26] These types of acquisitions involve ownership changes in many different markets, but often only minimal changes to local hospital concentration.[27] My results suggest that these types of mergers may still lead to higher hospital prices as a result of increased multimarket contact. In terms of policy implications, my results therefore suggest that hospital merger review should consider looking beyond just the local market when analyzing potential competitive effects. This implication is in line with the takeaways from other recent work on out-of-market hospital mergers (Dafny et al. (2016) and Lewis and Pflum (2016)) that also finds meaningful price effects via other channels.

One important weakness of my analysis is direct evidence of the underlying mechanism(s) through which multimarket contact can soften hospital competition. The theoretical literature demonstrates that multimarket contact can facilitate tacit collusion under a variety of circumstances, but I have been mostly unsuccessful in determining which, if any, are likely responsible for the effects I observe. A deeper understanding of the nuts and bolts of price determination in the industry may yield useful insights for this question as well as many others. To my knowledge, detailed analysis of actual hospital-insurer negotiations has been impeded by the confidential nature of the process, though recent litigation may make the inner workings of negotiations available for study, at least on a case-by-case basis.[28]

[26]See Evans, M. (2014, June 21). Consolidation creating giant hospital systems. *Modern Healthcare.*

[27]In addition, markets that would experience large changes in concentration as a result of the merger are often subject to divestiture requirements.

[28]For instance, the Idaho Statesman obtained hundreds of documents about negotiations between St. Luke's Health System and Blue Cross of Idaho. Dutton, A. (2015, July 4). Behind the scenes, St. Luke's and Blue Cross of Idaho fight for pricing power. *Idaho Statesman.*

References

Austin, P. C. (2011). Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. *Pharmaceutical statistics 10*(2), 150–161.

Bernheim, B. D. and M. D. Whinston (1990). Multimarket contact and collusive behavior. *The RAND Journal of Economics 21*(1), 1–26.

Boeker, W., J. Goodstein, J. Stephan, and J. P. Murmann (1997). Competition in a multimarket environment: The case of market exit. *Organization Science 8*(2), 126–142.

Busse, M. R. (2000). Multimarket contact and price coordination in the cellular telephone industry. *Journal of Economics & Management Strategy 9*(3), 287–320.

Capps, C., D. Dranove, and M. Satterthwaite (2003). Competition and market power in option demand markets. *RAND Journal of Economics 34*(4), 737–763.

Ciliberto, F. and J. W. Williams (2014). Does multimarket contact facilitate tacit collusion? inference on conduct parameters in the airline industry. *The RAND Journal of Economics 45*(4), 764–791.

Cuellar, A. E. and P. J. Gertler (2003). Trends in hospital consolidation: the formation of local systems. *Health Affairs 22*(6), 77–87.

Dafny, L. (2009). Estimation and identification of merger effects: An application to hospital mergers. *Journal of Law and Economics 52*(3), 523–550.

Dafny, L., K. Ho, and R. Lee (2016). The price effects of cross-market hospital mergers. *Working Paper*.

Dranove, D. and A. Sfekas (2009). The revolution in health care antitrust: new methods and provocative implications. *Milbank Quarterly 87*(3), 607–632.

Edwards, C. D. (1955). Conglomerate bigness as a source of power. In *Business concentration and price policy*, pp. 331–359. Princeton University Press.

Evans, W. N. and I. N. Kessides (1994). Living by the "golden rule": Multimarket contact in the us airline industry. *The Quarterly Journal of Economics 109*(2), 341–366.

Gaynor, M. and R. Town (2012). The impact of hospital consolidation–update. *The Synthesis Project, Robert Wood Johnson Foundation*.

Gowrisankaran, G., A. Nevo, and R. Town (2015). Mergers when prices are negotiated: Evidence from the hospital industry. *American Economic Review 105*(1), 172–203.

Ho, K. and R. S. Lee (2017). Insurer competition in health care markets. *Econometrica 85*(2), 379–417.

Kobayashi, H. and K. Ohta (2012). Optimal collusion under imperfect monitoring in multimarket contact. *Games and Economic Behavior 76*(2), 636–647.

Lewis, M. S. and K. E. Pflum (2015). Diagnosing hospital system bargaining power in managed care networks. *American Economic Journal: Economic Policy 7*(1), 243–274.

Lewis, M. S. and K. E. Pflum (2016). Hospital systems and bargaining power: evidence from out-of-market acquisitions. *RAND Journal of Economics, forthcoming*.

Li, J. and M. Powell (2015). Multilateral cooperation under uncertainty. *Working Paper*.

Matsushima, H. (2001). Multimarket contact, imperfect monitoring, and implicit collusion. *Journal of Economic Theory 98*(1), 158–178.

Melnick, G. and E. Keeler (2007). The effects of multi-hospital systems on hospital prices. *Journal of Health Economics 26*(2), 400–413.

Miller, N. and M. Weinberg (2017). Understanding the price effects of the miller/coors joint venture. *Econometrica, forthcoming*.

Rubin, D. B. and N. Thomas (2000). Combining propensity score matching with additional adjustments for prognostic covariates. *Journal of the American Statistical Association 95*(450), 573–585.

Schmitt, M. (2017). Do hospital mergers reduce costs? *Journal of Health Economics 52*, 74–94.

Scott, J. T. (1982). Multimarket contact and economic performance. *The Review of Economics and Statistics 64*(3), 368–375.

Sekiguchi, T. (2015). Multimarket contact under demand fluctuations. *International Journal of Game Theory 44*(4), 1033–1048.

Spagnolo, G. (1999). On interdependent supergames: multimarket contact, concavity, and collusion. *Journal of Economic Theory 89*(1), 127–139.

Stephan, J., J. P. Murmann, W. Boeker, and J. Goodstein (2003). Bringing managers into theories of multimarket competition: Ceos and the determinants of market entry. *Organization Science 14*(4), 403–421.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical science: a review journal of the Institute of Mathematical Statistics 25*(1), 1.

Vistnes, G. S. and Y. Sarafidis (2013). Cross-market hospital mergers: A holistic approach. *Antitrust Law Journal 79*(1), 253–293.

Waldfogel, J. and J. Wulf (2006). Measuring the effect of multimarket contact on competition: Evidence from mergers following radio broadcast ownership deregulation. *The BE Journal of Economic Analysis & Policy 5*(1), 1–23.

Yu, T. and A. A. Cannella (2013). A comprehensive review of multimarket competition research. *Journal of Management 39*(1), 76–109.

7 Appendix

7.1 Traditional analysis

In this section, I examine regression specifications similar to those commonly utilized in the empirical multimarket contact literature (e.g., Evans and Kessides (1994) and Waldfogel and Wulf (2006)). While these specifications are subject to the identification concerns discussed in the main text, they bolster the main findings of the paper by demonstrating that a positive, statistically significant relationship between multimarket contact and prices is often present when estimating models more similar to those of the existing literature.

The basic estimating equation is a fixed effects model of the form:

$$\ln\left(\text{price}_{hjt}\right) = \theta_j + \gamma_t + \lambda \cdot MMC_{jt} + X_{hjt}\beta + \varepsilon_{hjt}\,, \tag{4}$$

where h is hospital, j is market, and t is year. In addition to a market level measure of multimarket contact (MMC_{jt}), the estimating equation includes market fixed effects (θ_j), year fixed effects (γ_t), and other hospital and/or market level controls (X_{hjt}). Since the estimating equation includes market fixed effects, the effect of multimarket contact (λ) is identified by within-market changes in multimarket contact over time.

Market definition

I estimate equation (4) using two common ad hoc market definitions that are typically thought to bound the "ideal" market definition. The first market definition, hospital referral region (HRR), splits the country into 306 distinct areas. HRRs are defined using data about where Medicare patients go to receive major cardiovascular surgery and neurosurgery. Each HRR contains at least one city where both types of major surgery are performed, and therefore tend to be somewhat large. In most cases, HRRs are likely larger than the ideal market definition in that they include more hospitals than the ideal market definition would include. The second market definition, hospital service area (HSA), splits the country into more than 3,000 distinct areas. HSAs are collections of zip codes in which Medicare beneficiaries living in those zip codes receive most of their hospital care from hospitals in that area. Since hospital care tends to be delivered locally, HSAs are far smaller than HRRs. In most cases, HSAs are likely smaller than the ideal market definition in that they include fewer hospitals than the ideal market definition would include.

Multimarket contact measures

I also examine several different multimarket contact measures. The first, $AvgMMC$, is as defined in the text in Section 2.2: the average number of market overlaps per pair of owners in a market. Notably, $AvgMMC$ assigns equal weight to all pairs of owners in a market. Alternatively, it may be that multimarket contact between dominant hospitals in a market matters more than contact between smaller hospitals. I construct two additional measures to explore this possibility. The first, $WgtMMC$, weights the pair-specific market overlaps according to the total discharges of the pair (rather than taking the simple average like $AvgMMC$). The second, $TopAvgMMC$, computes the measure after excluding "small" hospital owners, where small is defined by sorting owners from largest to smallest in terms of discharges and eliminating all owners after 75% of total discharges in the market have been accounted for.

Last, another type of multimarket contact measure uses the number of other markets in which competitors overlap as a percentage of the total other markets in which those competitors operate. For instance, suppose that two owners in a market, A and B, overlap in one other market. Including the other overlapping market, suppose that A competes in two other markets and B competes in four other markets. Alternative measures of multimarket contact can be constructed with different ways of combining the percentage of A's other markets in which B is present (50%) with the percentage of B's other markets in which A is present (25%). One option is to take the maximum (Ciliberto and Williams (2014)) and then average over the pairs of owners in the market, a measure which I refer to as $PctAvgMMC$. While positively correlated, the primary difference between the measures based on counts of markets with overlap compared to percentages of markets with overlap is in how competition between national hospital systems affect the measures. For instance, in 2010, Community Health Systems (CHS) and the Hospital Corporation of America (HCA) operated in 78 and 59 HRRs, respectively, overlapping in 21. For measures based on counts, this overlap is sizable, while for measures based on percentages the overlap represents only 27% of CHS' markets and 36% of HCA's.

Control variables

I utilize controls X_{hjt} similar to those used in the main text. To account for changes in the price measure driven by service and patient mix, I include (log) case mix index, the fraction of total discharges accounted for by Medicaid (% Medicaid), and (log) total beds. I include for-profit status and HHI (calculating shares using beds) to control for any contemporaneous changes in for-profit presence and/or market concentration. Last, while time-invariant differences between markets that attract large hospital systems are swept away by the market fixed effects, it may be that the hospitals of these systems and the markets containing them have different price trends than other hospitals and markets for reasons unrelated to multimarket contact.[29] I control for the presence of systems by adding the (log) discharge weighted average number of markets in which owners in a given market compete ("system span"). Intuitively, the idea behind adding the system span control is for identification to come specifically from markets where multimarket systems are not only present but also overlap with one another.

Results

Table 5 presents the results, with Panel A using HSA as the market definition and Panel B using HRR. The number of observations is much lower with HSA as the market definition because the multimarket contact measures are only defined for markets with multiple hospital owners. While few HRRs have only a single owner, the majority of HSAs have only a single owner. In odd-numbered columns, I estimate the model only including market and year fixed effects. In even-numbered columns, I add the control variables. The bottom row of each panel multiplies the point estimate of the effect of multimarket contact to the interquartile range of each measure, capturing the estimated price effect of moving from the 25th percentile to the 75th percentile of each measure.

Beginning with the first three multimarket contact measures ($AvgMMC$, $WgtMMC$, and $TopAvgMMC$), the results indicate a positive association between multimarket contact and prices. Most estimates are statistically significant at the 10% level or lower, and those that are not narrowly miss the cutoff. For instance, the p-values in columns (1) and (2) of Panel B are 0.109 and 0.184, respectively. While the results suggest a connection between multimarket contact and prices, the estimated magnitude of the effect is relatively small; moving from the 25th to the 75th percentile of the measures is estimated to increase prices by between 0.3 and 1.0 percent. That said, nearly $350 billion was spend on hospital care by private insurers in 2013,[30] so even a small percentage increase can be quite large in absolute terms.

The results for $PctAvgMMC$, on the other hand, yield noisy estimates that are statis-

[29] For instance, Melnick and Keeler (2007) find that system hospitals in California had faster price growth than non-system hospitals in the early 2000s, with the effect holding even in markets in which the system hospital did not have other system members in the same market.

[30] The Centers for Medicare & Medicaid Services, National Health Expenditure Accounts.

Table 5: Traditional MMC Regressions, 2000-2010

Panel A: HSA Market Definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AvgMMC	0.019*	0.025***						
	(0.010)	(0.009)						
WgtMMC			0.018**	0.025***				
			(0.008)	(0.007)				
TopAvgMMC					0.020***	0.019***		
					(0.005)	(0.004)		
PctAvgMMC							0.064	0.075
							(0.091)	(0.072)
Control variables		✓		✓		✓		✓
Observations	15,678	15,339	15,678	15,339	15,678	15,339	15,678	15,339
R-squared	0.356	0.562	0.356	0.562	0.356	0.562	0.356	0.562
25th to 75th %-ile price effect	0.4%	0.6%	0.5%	0.6%	0.3%	0.3%	0.2%	0.2%

Panel B: HRR Market Definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AvgMMC	0.015	0.017						
	(0.009)	(0.013)						
WgtMMC			0.027***	0.031*				
			(0.009)	(0.015)				
TopAvgMMC					0.015*	0.015		
					(0.008)	(0.012)		
PctAvgMMC							-0.089	-0.092
							(0.060)	(0.058)
Control variables		✓		✓		✓		✓
Observations	37,700	37,179	37,700	37,179	37,700	37,179	37,700	37,179
R-squared	0.203	0.539	0.203	0.539	0.203	0.539	0.203	0.539
25th to 75th %-ile price effect	0.3%	0.3%	0.9%	1.0%	0.8%	0.8%	-0.3%	-0.3%

Notes: ***p<0.01, **p<0.05, *p<0.10. Standard errors are clustered by state and observations are weighted by inpatient discharges. All specifications include market and year fixed effects. The included control variables are (log) Case Mix Index, % Medicaid, (log) Beds, For-Profit status, HHI, and (log) system span.

tically indistinguishable from zero and of varying sign. As discussed above when defining the measures, recall that overlap between large hospital systems is much more relevant for $AvgMMC$, $WgtMMC$, and $TopAvgMMC$ than it is for $PctAvgMMC$. Thus, the non-results for $PctAvgMMC$ accentuate the point that, to the extent multimarket contact meaningfully affects competition in the industry, it does so primarily via the behavior of large hospital systems.

7.2 Main result robustness: hospitals treated only once

The table below reports results after restricting the treatment group to hospitals treated only a single time during the period (205 hospitals). The results can be compared to Table 2, which reports results for the full treatment group (347 hospitals).

Panel A: Post Only (Equation (2))

	Control Group:			
	All	All	Matched	Matched
Post ($t \geq \tau_h$)	0.075***	0.079***	0.055**	0.060**
	(0.022)	(0.022)	(0.026)	(0.026)
Control variables		✓		✓
Hospitals	2,864	2,857	410	410
Observations	37,816	37,538	6,201	6,137
R-squared	0.770	0.773	0.737	0.740

Panel B: Leads & Lags (Equation (3))

	Control Group:			
	All	All	Matched	Matched
$t \leq \tau_h - 4$	-0.009	-0.011	0.001	-0.002
	(0.039)	(0.039)	(0.041)	(0.041)
$t = \tau_h - 3$	0.014	0.009	0.016	0.010
	(0.031)	(0.031)	(0.030)	(0.030)
$t = \tau_h - 2$	-0.003	-0.005	0.002	0.000
	(0.031)	(0.031)	(0.031)	(0.031)
$t = \tau_h - 1$	0	0	0	0
	–	–	–	–
$t = \tau_h$	0.051*	0.050	0.055*	0.055*
	(0.030)	(0.031)	(0.031)	(0.032)
$t = \tau_h + 1$	0.068**	0.067**	0.064**	0.064**
	(0.031)	(0.032)	(0.032)	(0.032)
$t = \tau_h + 2$	0.059*	0.062*	0.057*	0.060*
	(0.033)	(0.034)	(0.034)	(0.034)
$t = \tau_h + 3$	0.058*	0.058	0.046	0.047
	(0.035)	(0.035)	(0.035)	(0.035)
$t \geq \tau_h + 4$	0.085**	0.090**	0.065	0.070*
	(0.037)	(0.037)	(0.039)	(0.039)
Control variables		✓		✓
Hospitals	2,864	2,857	410	410
Observations	37,816	37,538	6,201	6,137
R-squared	0.770	0.773	0.737	0.740

Notes: ***p<0.01, **p<0.05, *p<0.10. Standard errors are clustered by hospital and observations are weighted by inpatient discharges. All specifications include hospital and year fixed effects. The included control variables are (log) Case Mix Index, % Medicaid, (log) Beds, For-Profit status, HHI, and a count of other system members. In Panel B, $t = \tau_h - 1$ (the year before treatment) is the omitted category.

7.3 Data construction

Hospital prices (HCRIS)

$$\text{non-Medicare price} = \frac{\text{inpatient charges} \cdot \big(1 - \text{discount factor}\big) - \text{Medicare payments}}{\text{total inpatient discharges} - \text{Medicare discharges}} \tag{5}$$

There was a change to the cost report forms in 2010. Therefore, I list the line items for both the original form (1996 format) and the new form (2010 format).

- **Inpatient charges:** Worksheet G-2, Parts 1 & 2, the sum of:
  - Hospital general inpatient routine care services revenue: line 1, column 1 (1996); line 1, column 1 (2010)
  - Total intensive care type inpatient hospital services revenue: line 15, column 1 (1996); line 16, column 1 (2010)
  - Inpatient ancillary services revenue: line 17, column 1 (1996); line 18, column 1 (2010)
- **Discount factor:** Worksheet G-3, the ratio of:
  - Contractual allowances and discounts on patients' accounts: line 2, column 1 (1996); line 2, column 1 (2010)
  - Total patient revenues: line 1, column 1 (1996); line 1, column 1 (2010)
- **Medicare payments:** Worksheet E, Part A, the sum of:
  - Total amount payable for program beneficiaries: line 18, column 1 (1996); line 61, column 1 (2010)
  - Primary payer payments: line 17, column 1 (1996); line 60, column 1 (2010)
- **Total inpatient discharges:** Worksheet S-3, Part 1
  - Inpatient discharges, all patients: line 12, column 15 (1996); line 14, column 15 (2010)
- **Medicare discharges:** Worksheet S-3, Part 1
  - Inpatient discharges, Title XVIII: line 12, column 13 (1996); line 14, column 13 (2010)

Medicare prices are calculated as Medicare payments divided by Medicare discharges, using the line items given above.

Combining American Hospital Association and Irving Levin data

In this section, I briefly describe how I construct the hospital ownership data used throughout the paper. The standard source for hospital ownership information is the American Hospital Association (AHA) *Annual Survey of Hospitals*, which contains a field with reported system identification. I create a second system identification variable using the Irving Levin & Associates *Hospital Acquisition Report*. This second system identification variable is created by fixing hospital ownership as it is reported in 2012 in the AHA survey, and then rolling back all hospital M&A from 1998 and on that was tracked by Irving Levin. The new system identification variable changes for a given hospital only when that hospital was acquired as part of a transaction contained in the Irving Levin reports. These two system identification variables – one from the AHA data and the second created using the Irvin Levin data – differ from one another in at least one year for around 30% of hospitals in the data. In these cases, I searched news stories, archived hospital websites, etc. to try to resolve all discrepancies. The resulting system identification variable – which combines the AHA data, the Irving Levin reports, and independent research – is what I use to track hospital ownership. The final variable matches the original AHA system identification for about 90% of observations, but is likely more accurate in terms of ownership *changes*, which is crucial in studies of the effects of hospital M&A.

Other data construction notes

Below I list several other elements of the data construction process not discussed in the text.

- Besides general acute care hospitals, the HCRIS data also contains information data on long-term care, psychiatric, etc. hospitals as well. I limit the sample to general acute care hospitals based on a hospital's (a) Medicare provider number and (b) service type in the AHA data.
- I limit the data to hospitals in the 50 states and Washington, DC and drop military, Veterans Affairs, and Indian Health Service hospitals.
- The non-Medicare price calculated from the HCRIS data can be quite noisy, so it is standard practice to eliminate outliers from the measure (e.g., see Dafny (2009) and Lewis and Pflum (2016)). I winsorize prices at the 5th and 95th percentiles in order to avoid dropping observations. The reported results in Section 4.6 are robust to making no corrections for outliers (a post coefficient of 0.080, significant at the 1% level) and dropping rather than winsorizing outliers (a post coefficient of 0.062, significant at the 1% level).

7.4 Optimal matching

In the final sample, there are 347 treatment hospitals and 2,603 potential control hospitals. A match can therefore be described by a 903,241 (=347*2,603) element vector – one element for each possible treatment and control pair. The elements corresponding to matched pairs take a value of 1, while the elements corresponding to unmatched pairs take a value of 0. Formally, the matching problem is given by:

$$\min_{\boldsymbol{a}} \sum_{t=1}^{T} \sum_{c=1}^{C} a_{t,c} \cdot d(t,c) \quad s.t. \tag{6}$$

$$a_{t,c} \in \{0,1\} \quad \forall\, t, c \tag{6.1}$$

$$\sum_{c=1}^{C} a_{t,c} = k_1 \quad \forall\, t \tag{6.2}$$

$$\sum_{t=1}^{T} a_{t,c} \leq k_2 \quad \forall\, c \tag{6.3}$$

t indexes treatments and c indexes controls. $d(t,c)$ is a function that maps treatment-control pairings to a non-negative real number (the distance between the pair). The objective of (6) is thus to find the pairing of treatments and controls that minimizes the sum of the distances between the paired treatment and control hospitals. Constraint (6.1) imposes that each element of $\boldsymbol{a}$ is either 0 (unmatched) or 1 (matched) (binary integer constraints). Constraint (6.2) imposes that each treatment should be matched to k_1 controls. Constraint (6.3) imposes that each control should be matched to at most k_2 treatments.

For $d(t,c)$, I use the Mahalanobis distance with the following vector of covariates, each measured in 1998: non-Medicare price, total discharges, case mix index, % Medicaid, total beds, (own-hospital) HHI, and a count of other system members. I replace the Mahalanobis distance with a large number (larger than the maximum observed Mahalanobis distance) if the logit of the estimated propensity scores[31] differs by more than 0.2 standard deviations (the recommendation of Austin (2011)). I also require that the control hospital shares the same Metro status as the treatment and is in the same Census division. I set $k_1 = k_2 = 1$, so that each treatment is matched to a single control and each control is not permitted to be matched to more than one treatment.

[31]Propensity scores are estimated with a logit model of treatment as a function of the above covariates plus for-profit status.