Multimarket Contact in the Hospital Industry*

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Abstract

Hospitals in the U.S. increasingly belong to multihospital systems that operate in multiple 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., when firms compete with one another in several markets simultaneously. I test whether increases in multimarket contact over the 2000-2010 period caused increases in hospital prices. Across a variety of econometric analyses, including those that exploit plausibly exogenous variation in multimarket contact generated by *out-of-market* consolidation, I find that multimarket contact does lead to higher hospital prices. To date, academic research and antitrust enforcement has primarily focused on the effects of mergers that increase within-market hospital concentration. My results suggest that continued consolidation in the industry – especially mergers between large hospital systems – may lead to higher prices even if that consolidation entails only minimal changes to within-market concentration.

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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% (Dafny (2009)). With these effects in mind, antitrust authorities such as the Federal Trade Commission frequently investigate deals 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, about 37% of hospital mergers between 2000 and 2010 had no hospital referral region (HRR; a broad market definition) overlap between target and acquirer, and about 13% 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* lead to increases in hospital prices over the 2000-2010 period. As multihospital systems with geographic reach continue to grow – as of 2012, 46% of hospitals in my data belong to systems that operate in multiple HRRs and 36% 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]

[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). To my knowledge, the idea was first formalized by Bernheim and Whinston (1990).

I begin the empirical analysis by studying the relationship between the average level of multimarket contact between owners in a market (see Section 2.2 for the exact definition of this measure) and hospital prices. To do so, I estimate specifications with market fixed effects that exploit within-market variation in multimarket contact (over time), as is standard in the existing empirical literature on multimarket contact (e.g., Evans and Kessides (1994)). Using two alternative market definitions (Hospital Referral Region and Hospital Service Area), I find evidence of a statistically significant, positive relationship between multimarket contact and hospital prices. Further, I find that the effect of multimarket contact on pricing appears to be limited to the hospitals *directly* affected by multimarket contact – i.e., the hospitals belonging to the systems that overlap in multiple markets. However, the estimated magnitude of the effect of multimarket contact is small. In particular, the estimates imply that hospital prices in 2010 are less than 0.5% higher than they would have been absent the changes in multimarket contact that occurred during the preceding 10 years.

The main identification concern in these regressions is that within-market changes in multimarket contact may be endogenous. For illustration, 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. In the initial analysis, 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 in the initial analysis will bias the estimates of the effect of multimarket contact on prices. While I can control for other price drivers to some degree, it is unlikely that I can fully address endogeneity concerns by controlling for observable hospital and market characteristics.

In the second stage of the empirical analysis, 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 the effect of

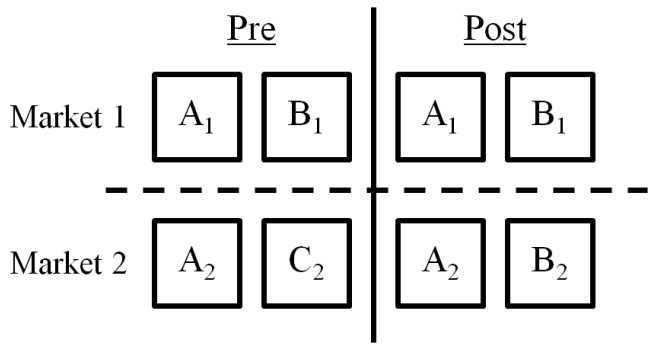

Figure 1: Two Market, Two Hospital Example The left panel (pre) depicts hospital ownership prior to the acquisition of hospital C_2. The right panel (post) depicts hospital ownership after hospital C_2 is acquired by system B. After the acquisition, systems A and B compete with one another in both markets.

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 again 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 5 to 7 percent. Further, specifications using exposure to an increase in multimarket contact generated by out-of-market M&A as an instrument for multimarket contact in the initial analysis imply price effects several times larger than the initial estimates. These results increase the economic significance of the estimated multimarket contact effect, and suggest that the estimates using the traditional methods (i.e., the methods commonly used in prior empirical work) may be conservative.

Recent mergers between large, national hospital systems entail increases in multimarket contact that are much larger than the changes induced by the typical merger during my study period. My results suggest that these 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 (Lewis and Pflum (2014) and Dafny et al. (2015)). 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 provide evidence that mergers can soften competition via coordinated effects, corroborating recent work by Miller and Weinberg (2015) 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 within-market concentration and multimarket contact. Section 3 discusses two 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 estimate panel data specifications that are similar to those that are commonly estimated in the empirical multimarket contact literature. In Section 5, I exploit changes in multimarket contact driven by out-of-market mergers, primarily in a difference-in-differences framework. In Section 6, I further refine these specifications to distinguish the effects of multimarket contact from other proposed mechanisms through which out-of-market mergers may affect prices. Section 7 summarizes and concludes.

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 a market for hospital services (see Dranove and Sfekas (2009) for a nice review of the issues). I return to this question in Section 4.0.2 when discussing the regression analysis, but for the purposes of the descriptive statistics here I utilize the Dartmouth Atlas' *hospital referral region* (HRR) which splits the U.S. into 306 distinct regions.[4]

The data sources used to generate the statistics shown here are described in detail in the data appendix in Section 8.4. Importantly, my 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 *Health Care Acquisition Report*, and (c) archived news stories and hospital websites. Comprehensive ownership information is needed to accurately compute measures of multimarket contact.

[4]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.

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 1,500), moderately concentrated (between 1,500 and 2,500), and highly concentrated (above 2,500). 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 ballooned over the same period, from 43% in 2000 up 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.[5]

2.2 Effects on multimarket contact

Besides the effects of hospital consolidation on within-market concentration 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 used in the empirical literature on multimarket contact (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.[6] Let mmc_{kmt} denote the number of markets 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:

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

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. In (1), I subtract one from mmc_{kmt} for

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

[6] I discuss other possible measures of multimarket contact in Section 4.1.2; this measure is sufficient for the purposes of the descriptive statistics shown here.

each pair so that the measure captures the number of *other* markets (besides j) in which owners k and m compete. For example, if no pair of owners in a market also competes in another market, then $AvgMMC$ will be equal to zero.

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

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 for the year 2012, successively treating the hospitals of multihospital systems as independent. I performed the calculation dissolving systems both from biggest to smallest (in terms of hospitals owned, breaking ties by hospital beds) and vice versa. In 2012, the mean of $AvgMMC$ across HRRs was 0.45. After treating the hospitals of the 10 biggest systems as independent, the mean of $AvgMMC$ across HRRs drops to 0.04 (see the top panel of the figure). In short, multimarket contact in the industry is largely driven by national hospital systems such as the Hospital Corporation of America (HCA), Community Health Systems (CHS), and Ascension Health (among others). If the hospitals of these systems were independent, there would be very little remaining multimarket contact in the industry. Another relevant question is whether multimarket contact is driven entirely by competition between national systems, or if competition between national systems and regional systems also plays a meaningful role. As shown in the bottom panel of the figure, the majority of multimarket contact is driven by national systems. For instance, the mean of $AvgMMC$ across HRRs is over 60% of its true value even after dissolving all but the top 30 systems. That said, competition

[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.

between national systems and regional systems does contribute to multimarket contact, as the mean of $AvgMMC$ across HRRs steadily decreases as small and medium sized systems are dissolved.

3 Multimarket Contact and Obstacles to Collusion in the Hospital Industry

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 of the question 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 collusive prices, but also increase the gains from deviation. Therefore, it is not clear that additional markets necessarily facilitate collusion. However, under a variety of plausible conditions – differences in growth rates across markets, stochastic demand fluctuations, differences in production costs across markets, concavity of firms' objective functions, etc. – multimarket contact improves the ability of firms to tacitly collude.[8]

There is a large body of empirical evidence from several industries consistent with the mutual forbearance hypothesis.[9] However, the hospital industry is different from many previously studied industries in several meaningful ways that may affect the ability of multimarket

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

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

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 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 (or are told to consider) multimarket contact when acting. 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 discuss each condition in turn, arguing that hospitals can plausibly overcome these obstacles.

3.1 Observability of price

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 (2015) assume either that prices are perfectly 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' actions.

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, who are responsible for the majority of multimarket contact in the industry, coordinating prices across hospitals within the system is not an uncommon task. For instance, national insurers that serve multistate employers

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

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] For large hospital systems (including not-for-profit systems), there are typically division presidents that are responsible for overseeing hospital operations in several states, along with C-level executives who manage the entire organization. Coordination of prices may therefore be possible across system members spanning several states, and likely over the entire organization as well.

4 Traditional Analysis

Ultimately, whether or not multimarket contact is capable of affecting hospital competition is an empirical question. To that end, I begin by estimating specifications similar to those commonly utilized in the empirical multimarket contact literature. Early studies on 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.

Taking as given (a) a measure of price and (b) a market definition, the basic estimating equation is a fixed effects model of the form:

$$\ln\left(\text{price}_{hjt}\right) = \theta_j + \gamma_t + \lambda \cdot AvgMMC_{jt} + X_{hjt}\beta + \varepsilon_{hjt}, \tag{2}$$

where h is hospital, j is market, and t is year. In addition to a (market level) measure of multimarket contact ($AvgMMC_{jt}$), 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 $AvgMMC$ over time. While the market fixed effects eliminate any time-invariant differences between markets that could contaminate the estimate of λ, the key identification concern is that within-market changes in $AvgMMC$ may be correlated with unobserved determinants of hospital prices. I return to this issue below in section 4.0.3 when discussing the control variables (X_{hjt}) included in the estimation and again in section 5 in which I exploit plausibly exogenous variation in multimarket contact

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

driven by out-of-market consolidation.

4.0.1 Hospital prices

For a measure of price, I use an estimate of the average net revenue that a hospital receives per non-Medicare inpatient discharge. The same basic measure is used in several studies of hospital prices (beginning with Dafny (2009)), and is calculated using the Centers for Medicare & Medicaid Services (CMS) Healthcare Cost Report Information System (HCRIS) data.[12] All prices are adjusted to 2010 dollars using the consumer price index for all urban consumers. Section 8.4.1 in the appendix contains more details about the exact line items used to calculate the measure.

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 this 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. As discussed below, I include several variables in X_{hjt} to attempt to control for aspects of the price formula that do not capture true price differences but rather differences in payer and/or service mix.

4.0.2 Market definition

Measurement of multimarket contact requires a market definition. 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

[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.

and in the courts. In merger cases, defining the market is an extremely fact-intensive process; doing so exhaustively for every hospital (and year) in the data is not feasible. Therefore, I estimate equation (2) using two common ad hoc market definitions that are typically thought to bound the "ideal" market definition. The first, hospital referral region (HRR), splits the country into 306 distinct areas. HRRs are defined using data on 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, 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.

Table 1 contains summary statistics from the year 2010 about both market definitions. One wrinkle is that $AvgMMC$ is undefined for markets with a single owner. In 2010, only a single HRR was monopolized, whereas more than 85% of HSAs were monopolized. Estimation occurs only using data from the non-monopolized markets, so summary statistics for HSAs are broken out for the non-monopolized HSAs. Unsurprisingly, HSAs with multiple owners tend to be much larger than the overall average in terms of hospitals, beds, and discharges. HRRs are also much larger than HSAs, even when considering only the HSAs with multiple owners. In 2010, HRRs contained an average of 14.3 hospitals while HSAs contained only 3.5.

4.0.3 Control variables

The measure of price that I use aggregates over all inpatients seen by a hospital, includes non-commercial payers such as Medicaid, and estimates contractual discounts using data on both inpatient and outpatient visits. To reduce the variation in price owing to these factors, I include controls for (log) case mix index, (log) total cost per discharge, (log) total beds, the fraction of total discharges accounted for by Medicaid, the fraction of total gross revenue accounted for by outpatient visits, and for-profit status. I include case mix, cost per discharge, and total beds to control for variation in price due to service and patient mix. I expect all three variables to positively influence prices. I include percent Medicaid to control

for variation in price due to Medicaid reimbursements. Since Medicaid reimburses hospitals at rates far below commercial insurance, I expect this variable to be a negative predictor of price. I include outpatient gross revenue share to control for the fact that estimated discounts in the price formula include discounts on revenue from both inpatient and outpatient visits. If discounts (as a ratio of charges) tend to be larger for outpatient procedures than inpatient ones, then this variable will likely be a negative predictor of price. I include for-profit status in the event that for-profit and not-for-profit hospitals have different pricing practices.

The inclusion of market fixed effects in the estimating equation reduces endogeneity concerns to within-market changes in multimarket contact. One remaining concern is that multimarket contact is affected by entry and exit patterns that may independently have an effect on prices via changes in market concentration. I therefore include HHI (calculating shares using beds) to control for changes in market concentration. I expect increases in HHI to increase prices. Another concern is that, as discussed in Section 2.2, multimarket contact is driven by large, national hospital systems. While time-invariant differences between markets that attract such 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.[13] I control for the presence of systems in two ways. First, I control for the (log) discharge weighted average number of markets in which owners in a given market compete ("system span"), which is positively correlated with multimarket contact. Second, I include system by year fixed effects for the 20 systems who owned the most hospitals per year on average over the 2000 to 2010 period. These fixed effects flexibly control for the pricing behavior of the systems that are most responsible for multimarket contact in the industry.

4.1 Results

Since the price variable is defined at the hospital-year level and $AvgMMC$ varies only by market-year, it is important to cluster standard errors at least at the market level. To maintain the same clustering across specifications and since errors may be correlated across markets within a broader geography, I cluster standard errors at the state level. I also weight observations by total discharges – the results are extremely similar when estimating without weights. Table 2 presents the results. In columns (1) to (3), HRR is the market definition.

[13] 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.

In columns (4) to (6), HSA is the market definition. In columns (1) and (4), I estimate the model only including the hospital-level control variables whose main purpose is to reduce the error variance in order to increase the precision of the estimate of the coefficient on $AvgMMC$. In columns (2) and (5), I add market HHI and (log) system span. In columns (3) and (6), I add the system by year fixed effects for the 20 biggest hospital systems.

For all six specifications, the estimated effect of $AvgMMC$ on hospital prices is positive and statistically significant at the 5% level. The control variables also typically have their expected sign, though it is somewhat surprising that the coefficient on HHI is not statistically significant. As highlighted in several academic studies (e.g., Dranove and Ody (2015)), it may be that HHI is not a particularly reliable measure of provider market power. While HRRs are likely larger than the ideal market definition and HSAs are likely smaller, it is not correct to interpret the HRR estimates as a lower bound for the effect of multimarket contact and the HSA estimates as an upper bound. Changing the market size tends to affect both the numerator (the total amount of multimarket contact) and the denominator (pairs of owners) of $AvgMMC$. Therefore, it is not the case that perturbing the market size from its optimal level necessarily dilutes or concentrates the measurement of multimarket contact.

To understand whether the estimated effects are economically meaningful, I applied the point estimates from Table 2 to (1) the difference in $AvgMMC$ between the 25th and 75th percentiles across hospitals (in 2010) and (2) the change in the mean $AvgMMC$ across hospitals from 2000 to 2010. The first interpretation highlights the broader effects of multimarket contact on hospital prices while the second interpretation highlights the effects of changes in multimarket contact that occurred during the period (largely due to hospital M&A). For both market definitions, moving from the 25th to the 75th percentile of multimarket contact entails an increase in $AvgMMC$ of around 0.25. Applied to the point estimates in Table 2, this movement is estimated to increase prices by 0.4 to 0.6 percent. The mean $AvgMMC$ across hospitals increased from 2000 to 2010 by about 0.08 for the HRR market definition and 0.02 for the HSA market definition. These changes imply that prices on average are between 0 and 0.2 percent higher in 2010 than they would have been absent the changes in multimarket contact that occurred during the period.[14] In short, according to the initial estimates, the effect of multimarket contact on hospital pricing is statistically distinguishable from zero but the magnitude of the effect is quite small.

[14]With the HSA market definition, estimated average price changes are diluted by the fact that less than 40 percent of hospitals belong to an HSA with multiple owners. However, even computing the price changes only over affected hospitals, the estimated magnitude of the multimarket contact effect is still less than 0.1 percent.

4.1.1 Separating own and competitor multimarket contact

In equation (2), I assume (following the literature) that what matters for the pricing of hospital h is the overall level of multimarket contact in the market, regardless of the source of that contact. For example, suppose that three hospitals with different owners – A, B, and C – compete in a market. For all three hospitals, $AvgMMC$ takes the same value, even if multimarket contact entirely comes from the A/B pair (for instance). In that case, it may be that the primary effect of multimarket contact is to increase prices at hospitals A and B. The price of hospital C may also be affected indirectly, e.g. if prices are strategic substitutes as in standard models,[15] but perhaps by not as much. To investigate this possibility, I calculate two additional measures of multimarket contact: (1) $OwnAvgMMC_{ht}$, which is the same as $AvgMMC_{jt}$ (for the j in which h operates) but computed only for pairs of owners containing h, and (2) $OthAvgMMC_{ht}$, which is the same as $AvgMMC_{jt}$ but computed only for pairs of owners *not* containing h.[16]

I then estimate:

$$\ln\left(\text{price}_{hjt}\right) = \theta_j + \gamma_t + \lambda_{own} \cdot OwnAvgMMC_{ht} + \lambda_{oth} \cdot OthAvgMMC_{ht} + X_{hjt}\beta + \varepsilon_{hjt}. \quad (3)$$

Table 3 gives the estimates of equation (3), mirroring the structure of Table 2.[17] To begin, note that the number of observations drops compared to the numbers in Table 2. Since $OthAvgMMC$ computes multimarket contact between other owners in a market, for there to be at least one pair of other owners there must be at least three owners in the market. As a result, a handful of HRRs and several hundred HSAs are dropped. Looking at the coefficients on the multimarket contact variables, the results suggest that multimarket contact

[15] 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 patients 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.

[16] Let o_{ht} denote the owner of hospital h in year t and $\mathcal{F}_{ht}$ denote the set of owners in the market in which h operates in year t (including the owner of h). Formally,

$$OwnAvgMMC_{ht} = \frac{1}{|\mathcal{F}_{ht}| - 1} \sum_{m=1}^{N} \mathbb{1}\left[m \in \mathcal{F}_{ht}, m \neq o_{ht}\right] \cdot \left(mmc_{o_{ht}mt} - 1\right) \quad \text{and}$$

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

[17] I have also estimated equation (3) replacing the market fixed effects with hospital fixed effects. Inclusion of hospital fixed effects partially attenuates the estimated coefficient on $OwnAvgMMC$, but the effect remains positive and statistically significant.

between a given hospital and its competitors is what matters for pricing: the coefficients on $OwnAvgMMC$ are positive and significant for both market definitions, while the coefficients on $OthAvgMMC$ are not. Tests for the equality of λ_{own} and λ_{oth} reject the null hypothesis that the effects are equal at conventional significance levels.[18]

For magnitudes, moving from the 25th to 75th percentile of $OwnAvgMMC$ entails an increase of about 0.2 for both market definitions. Using the estimates in Table 3, this movement is estimated to increase prices by 0.8 to 1.2 percent for the HRR market definition and 1.6 to 1.9 percent for the HSA market definition. For the HRR market definition, the mean of $OwnAvgMMC$ across hospitals increased by about 0.08 from 2000 to 2010. Fixing the effect of $OthAvgMMC$ at zero, the point estimates therefore imply that prices on average are roughly 0.3 to 0.4 percent higher than they would have been absent the changes in multimarket contact that occurred during the period. Nearly two-thirds of hospitals do not experience any change in $OwnAvgMMC$ during the period, however. Among hospitals experiencing a change in $OwnAvgMMC$ over the period, the mean change in $OwnAvgMMC$ is about 0.22. For these hospitals, the results indicate price effects due to multimarket contact of about 0.8 to 1.2 percent (close to three times the overall average). With the HSA market definition, estimated effects remain negligible as there are fewer hospitals affected by multimarket contact and the overall changes in multimarket contact during the period are smaller.

4.1.2 Alternative measures of multimarket contact

I have also experimented with several other alternative measures of multimarket contact besides $AvgMMC$. A measure similar to $AvgMMC$, but which weights the pair-specific market overlaps according to the total discharges of the pair (rather than taking the simple average like $AvgMMC$), accounts for the idea that multimarket contact between dominant hospitals in a market might matter more than contact between smaller hospitals. This measure yields similar results to those reported above in all specifications; in fact, the effects tend to be stronger using the weighted measure.

Another type of alternative 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

[18] In columns (1) and (2) of Table 3, equality is rejected at the 1% level. In columns (3) to (5), equality is rejected at the 5% level. In column (6), equality is rejected at the 10% level.

B competes in four other markets. Several 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%), e.g. taking the product (Evans and Kessides (1994)) or the maximum (Ciliberto and Williams (2014)).

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 and the Hospital Corporation of America 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. Regression analyses replacing $AvgMMC$ with percentage based measures yield noisy estimates that are statistically indistinguishable from zero and of varying sign. These non-results accentuate the point that, to the extent multimarket contact meaningfully affects competition in the industry, it does so largely via the behavior of national hospital systems.

5 Exploiting Variation in Multimarket Contact from Out-of-Market M&A

As previously noted, the primary identification concern in the above analysis is that within-market changes in multimarket contact are endogenous. I attempted to control for two such possibilities – concurrent changes in concentration (by controlling for HHI) and differential price trends in markets containing large systems (by controlling for system size and top 20 system-year fixed effects) – and in both cases the estimated effect of multimarket contact remained very similar. That said, one may question whether multimarket contact is exogenous even conditional on these controls. In this section, I use out-of-market mergers as a plausibly exogenous source of variation in multimarket contact to estimate difference-in-differences models. Specifically, I examine prices 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 changes 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 acquired Deaconess Hospital, its first hospital in the Oklahoma City, OK metro area. Less than 10 miles away is St. Anthony Hospital, which is owned by SSM Health Care. In Mount Vernon, IL, CHS and SSM own hospitals less than 2 miles apart: Crossroads Community Hospital and Good Samaritan Regional Health Center. CHS' acquisition of Deaconess Hospital 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 Hospital, as compared to a set of control hospitals unaffected by multimarket contact; this is approximately what the previous specifications do. However, one might reasonably be concerned that the timing of the acquisition of Deaconess Hospital is correlated with unobserved determinants of hospital prices. For instance, if Deaconess Hospital was struggling financially prior to being acquired, we might have expected prices at Deaconess to either rebound in subsequent years or for Deaconess to exit, for reasons unrelated to (but correlated with) the increase in multimarket contact. Or, as suggested by Lewis and Pflum (2014) and Lewis and Pflum (2015), 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 Hospital. 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 would 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 is not 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 Community Hospital and Good Samaritan Regional Health Center. By examining price changes at hospitals that experience increases in multi-

market contact but are located away from the merger generating that increase, I can estimate an arguably causal effect of multimarket contact on prices. Drawing on the suggestive results in Section 4.1.1 that price increases are limited to hospitals directly affected by multimarket contact, I begin by looking at prices only at hospitals like Crossroads and Good Samaritan rather than other hospitals in the immediate area. I examine price effects at surrounding hospitals in Section 5.1.1.

To identify "treatment" hospitals (hospitals similar to Crossroads and Good Samaritan in the example), I start with the set of all acquired hospitals. I then find all hospitals within 20 miles of an acquired hospital.[19] 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 an exogenous increase in multimarket contact. Both acquired hospitals and hospitals that are within 20 miles of an acquired hospital 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 HRR 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.[20]

Denote the set of all treatment hospitals by $\mathcal{M}$, and let τ_h be the year in which a hospital was first treated (if ever). I keep the data for treatment hospitals in the three years before and after τ_h. I then estimate the following difference-in-differences model:

$$\ln\left(\text{price}_{ht}\right) = \alpha_h + \gamma_t + \lambda \cdot \mathbb{1}\left[t \geq \tau_h, h \in \mathcal{M}\right] + X_{ht}\beta + \varepsilon_{ht}, \tag{4}$$

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. 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 parsimony, I begin by estimating specifications without additional control variables X_{ht} – these controls are

[19] I use a fixed 20 mile radius rather than the fixed boundary market definitions HRR and HSA because it avoids issues in the HRR/HSA definitions at market boundaries.

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

less meaningful here than in equations (2) and (3) due to the inclusion of hospital fixed effects (there is far more between-hospital variation in the covariates than within-hospital variation).

The key identifying assumption when estimating equation (4) is that, absent treatment, treatment hospitals would have had the same price trends as controls (formally, that the post-treatment dummy variable $\mathbb{1}\left[t \geq \tau_h, h \in \mathcal{M}\right]$ is uncorrelated with the error term ε_{ht}). 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 (4) that includes treatment leads and lags:

$$\ln\left(\text{price}_{ht}\right) = \alpha_h + \gamma_t + \sum_{k=-3}^{3} \lambda_k \cdot \mathbb{1}\left[t = \tau_h + k, h \in \mathcal{M}\right] + X_{ht}\beta + \varepsilon_{ht}. \tag{5}$$

I omit the dummy corresponding to the year before treatment, $t = \tau_h - 1$. If the λ_k for $k = -3$ and $k = -2$ are close to zero and not trending upward, this means that treatment hospitals have similar price trends to controls prior to treatment, providing suggestive evidence that the parallel trends assumption holds.

5.0.1 Control hospitals

When choosing control hospitals, the goal is to find hospitals whose price trends arguably provide the right counterfactual price trends for treated hospitals (i.e., the trends treated hospitals would have followed but for treatment). I estimate equations (4) and (5) using several different control groups, each of which provides different benefits and drawbacks.

First, I use all other hospitals – except for hospitals that were acquired at some point during the period and hospitals like St. Anthony in the example – as controls. The primary benefit of this control group is in 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 (5) 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 treated hospitals.

Second, 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, North Carolina was never affected by changes in multimarket contact during the period (there is a single other hospital within 20 miles of Martin General, and there were no relevant ownership changes during the period). One major benefit of this "treated system" control group is that the control hospitals are much more similar in terms of system size and also presumably more similar in terms of unobservable factors influencing prices such as management practices. However, the treated system control hospitals tend to be smaller and more rural compared to the hospitals in the same system that are affected by changes in multimarket contact. If rural hospitals have different price trends than urban hospitals, for example, then my estimates of λ may again be biased.

Third, I use matching methods from the statistics literature to match treatment hospitals with similar hospitals from the all controls group.[21] 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 baseline covariates (1998 for the vast majority of hospitals) 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 (2011b)), 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 8.2 in the appendix.

Table 4 provides descriptive statistics about treatment hospitals and the hospitals in the three control groups. Compared to the treatment hospitals, hospitals in the all control group are smaller (discharges, beds, etc.) and less likely to belong to a system. Hospitals in the treated system control group are much more similar to the treatment hospitals in terms of system size, but are smaller and much more likely to be located in a rural area. For most covariates, hospitals in the matched control group are much more similar to the treatment hospitals, though they are less likely to be for-profit and tend to belong to smaller systems. To further evaluate the observable differences between treatment and control hospitals, Figure 6 plots the absolute standardized differences between treatment and control hospitals for each of variables listed in Table 4. For Census division and metro status, the differences are reduced to zero (by construction). With the exception of system size and for-profit status, the standardized differences for the remaining covariates are reduced to around 0.1 or less. My review of the literature indicates that absolute standardized differences less than 0.1 are

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

typically viewed as negligible differences between groups (Austin (2011a)).

5.1 Results

For all specifications, observations are weighted by total discharges and standard errors are clustered by hospital. Figure 7 plots the estimated λ_k coefficients after estimating equation (5) (without controls X_{hjt}). Table 5 presents the coefficient estimates from equation (4) in Panel A and from equation (5) in Panel B. For all three control groups, treatment hospitals share similar price trends to controls prior to treatment. In the year of treatment, prices at treatment hospitals jump up relative to controls and then continue to increase slightly in subsequent years. All told, the results indicate price increases between 5 and 7 percent as a result of treatment. To evaluate the robustness of these results to reasonable changes in the regression specification, I also estimated a battery of additional models to address various concerns with the main analysis. For instance, one may wonder if the results are robust to the inclusion of control variables X_{hjt} or changes in the market definition (i.e., adjusting the 20 mile radius). Details and results for each of these additional specifications are given in Section 8.3 in the appendix. Across all specifications, estimated treatment effects range from 3 to 7 percent.

I also estimated several additional specifications to attempt to uncover potential heterogeneity in treatment effects. Specifically, if the effect depends on: (1) for-profit status, (2) the share of beds in the area controlled by the hospitals experiencing the increase in multimarket contact, and (3) the change in multimarket contact relative to the pre-existing level of multimarket contact between the affected systems. In all three cases, I am unable to consistently reject the null hypothesis that the treatment effects are the same. While I suspect there are meaningful differences in the types of transactions that are likely to lead to increased prices, I have been unable to precisely detect these differences in my data.

To utilize the out-of-market identifying variation to estimate the aggregate impact of changes in multimarket contact on hospital prices over the period, I instrument for the own multimarket contact variable in equation (3) ($OwnAvgMMC_{ht}$) with $post_{ht}$. The two-stage-least-squares estimates are given in Table 6. The estimated coefficients are substantially larger than the corresponding estimates from Table 3. Downward bias in the original estimates is consistent with changes in multimarket contact often occurring in markets with weakening demand, which is corroborated by anecdotal evidence that national hospital systems often acquire hospitals in financial distress.[22] Using the instrumental variables esti-

[22]For instance, Health Management Associates posted a nearly $100 million dollar net loss in the third

mates, moving from the 25th to 75th percentile in terms of $OwnAvgMMC$ is estimated to increase prices by 2.5 to 5.9 percent, compared to 0.8 to 1.9 percent with the initial estimates. The estimated impact of changes in multimarket contact over the 2000 to 2010 period are also much larger. With the HRR market definition, prices on average are estimated to be between 0.9 and 1.6 percent higher as a result of changes in multimarket contact. Calculated only for hospitals experiencing a change in $OwnAvgMMC$ during the period (about one-third of hospitals), average estimated effects are nearly three times larger, between 2.4 and 4.4 percent. To summarize, after attempting to address the potential endogeneity of multimarket contact by exploiting changes in multimarket contact generated by out-of-market M&A, the estimated impact on prices becomes much more economically meaningful than the effects implied by the traditional analysis.

5.1.1 Hospitals in the same area as treatment hospitals

In Table 7, I include hospitals within 20 miles of treated hospitals as a separate treatment group. I estimate the specification both with simple post indicators and with three year leads and lags for both treatment groups. Both specifications use all other hospitals as the control group. The results are in line with the findings from the fixed effects regressions in Section 4.1.1: the effects of multimarket contact appear to be limited to hospitals directly affected by it, as the point estimates for the indirectly affected hospitals are typically small in magnitude and always statistically insignificant. A test for equality of the post coefficients rejects the null hypothesis that the effects are equal at the 1% level. Since prices between competing hospitals positively co-move in standard models, it is somewhat surprising that I am unable to find evidence of effects for hospitals in the same area as those directly affected by multimarket contact, though I may just lack the statistical power to detect the more nuanced effect.

5.1.2 Medicare price falsification test

Medicare pays hospitals according to a formula that does not depend on multimarket contact, but does depend on factors like area wage costs and procedure severity. If the observed price increases at treatment hospitals are due to coincident changes in things like wage costs or service mix, we would therefore expect treatment to affect the average revenue that treatment hospitals receive from Medicare patients ("Medicare prices"). If there is no effect

quarter of 2013 prior to being acquired by Community Health Systems. Source: Herman, B. (2013, November 13). HMA Loses $97M in Q3 as New Board, Glenview Approve CHS Merger. *Becker's Hospital CFO*.

of treatment on Medicare prices, it is more likely that the observed effects on 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. Table 8 shows the results from specifications that estimate equation (4) but with the log of Medicare price (Panel A) and the log of the ratio of non-Medicare to Medicare price (Panel B) as the dependent variable. I find no evidence of changes in Medicare prices: the point estimates in Panel A are all extremely close to zero and statistically insignificant. In Panel B, in which I directly control for changes in area wage costs, etc. by using the ratio of non-Medicare to Medicare price as the dependent variable, the results remain extremely similar to the results with non-Medicare price as the dependent variable (Panel A of Table 5).

6 Relationship to Lewis and Pflum (2014) and Dafny et al. (2015)

Several other recent papers provide alternative mechanisms besides multimarket contact through which hospital competition can potentially be linked across geographic markets. In this section, I argue that these alternative mechanisms are unlikely to be responsible for the effects I observe. Lewis and Pflum (2014) find that hospitals acquired by out-of-market systems increase by 14 to 18 percent compared to independent hospitals, and argue that the observed increases may be due to systems having greater bargaining power, irrespective of the local competitive environment. Since I exclude hospitals that were acquired at any point during the period in the difference-in-differences analysis, the system effect documented by Lewis and Pflum (2014) cannot be responsible for the results I observe. Moreover, adding controls for in-market acquisitions to the regressions in Section 4 also do not meaningfully impact the results.

Dafny et al. (2015) (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. 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 two different samples of 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 meaningful 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 much stronger within states than across them.

Of the results presented thus far, the possibility that DHL's mechanisms are responsible for the effects I observe is best addressed by the difference-in-differences results with the treated system control group (column 2 of Table 5). For that specification, 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 DHL's mechanisms, it is likely that the "control" hospitals in that specification will be affected as well. Yet, the results remain similar to what is observed with the other control groups, where the effects of DHL's mechanisms are less likely to be present.

I also estimated two additional specifications to attempt to distinguish between the effects of multimarket contact and the mechanisms developed by DHL. In the 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 DHL's mechanisms. In addition, I do not distinguish between the hospitals of the system that made the acquisition that triggered the increase in multimarket contact (hospitals like Crossroads in Figure 5) and hospitals without any change to the system (hospitals like Good Samaritan in Figure 5). DHL's mechansisms may predict price effects for hospitals of the system making the acquisition, but not for the other hospitals (except potentially through the strategic complementarity of price). To further refine the specifications in order to isolate cases that are predicted to have price effects as a result of multimarket contact but not as a result of DHL's mechanisms, I interacted the post-treatment dummy variable $post_{ht}$ with indicators for whether: (1) the acquisition triggering the increase in multimarket contact occurred in-state or out-of-state,[23] and (2) the treated hospital belongs to the system that made the acquisition triggering the increase in multimarket contact.

Table 9 gives the results. Panel A shows the results for the specification splitting the treatment group by whether the increase in multimarket contact was generated by an in-state or out-of-state acquisition. Panel B shows the results for the specification splitting the treatment group by whether the increase in multimarket contact was generated by an

[23] About 60% of treatment hospitals were treated by in-state acquisitions, while the remaining 40% were treated by out-of-state acquisitions.

acquisition of the treatment hospital's own system. The point estimates for the in-state and out-of-state treatment groups are positive, statistically significant, and of similar magnitude. The out-of-state treatment group is less likely to be affected by DHL's mechanisms than the in-state treatment group, so these results suggest that the multimarket contact effect is distinct from DHL's mechanisms. The point estimates for the acquirer and non-acquirer treatment groups are also positive, statistically significant, and of similar magnitude. While the hospitals in the non-acquirer treatment group are not directly affected by DHL's proposed mechanisms, they may be affected indirectly: if hospitals in the acquiring system treatment group gain market power and are able to negotiate higher prices, surrounding hospitals will also tend to be able to negotiate higher prices in turn. However, recall that I did not find evidence that hospitals surrounding treatment hospitals experience price changes (see Table 7). Therefore, for DHL's mechanisms to generate the observed treatment effect for hospitals of the non-acquiring systems, it would need to be the case that any indirect effects apply only to those hospitals and not other hospitals in the area. This possibility would be more likely if, for example, hospitals in the acquiring system treatment group are more substitutable with hospitals in the non-acquiring system treatment group than other hospitals in the surrounding area. That said, I have not found clear evidence suggesting differences in substitutability between the groups: for example, all three groups are similar in terms of mean and median bed size and total discharges. In short, I believe that the observed treatment effect for hospitals of non-acquiring systems is more likely to be generated by the effects of multimarket contact than any indirect effects of DHL's proposed mechanisms.

To summarize, I believe that my results accurately reflect the impact of multimarket contact on prices, rather than spuriously capturing the impact of other mechanisms through which out-of-market M&A could affect hospital competition.

7 Conclusion

In this paper, I find evidence that multimarket contact leads to higher hospital prices. Specifications common in the empirical literature that exploit within-market variation in multimarket contact reveal a statistically significant and positive effect of multimarket contact on hospital prices. To address the potential endogeneity of within-market changes in multimarket contact, I estimate difference-in-differences (and instrumental variables) models that isolate variation in multimarket contact generated by out-of-market consolidation. If out-of-market consolidation is orthogonal to unobserved determinants of in-market prices, then

this approach allows me causally estimate the effect of multimarket contact on prices. As with the first set of results, I find a positive and statistically significant effect of multimarket contact on prices. However, the estimated magnitude of the multimarket contact effect increases substantially compared to the first set of estimates, suggesting that the initial estimates may be biased downwards. Using the most aggressive estimates, I estimate that prices in 2010 are on average about 1.6% higher than they would have been absent the increases in multimarket contact that occurred during the period. While relatively small in percentage terms, nearly $350 billion was spent on hospital care by private insurers in 2013,[24] so a 1.6% increase corresponds to more than $5 billion in increased spending.[25]

Moreover, there have been several recent high-profile mergers between national hospital systems beyond my study period that have further increased the extent of multimarket contact in the industry.[26] For instance, 135 hospital Community Health Systems completed its acquisition of 71 hospital Health Management Associates in January 2014. 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 the increased multimarket contact. In terms of policy implications, my results therefore suggest that hospital merger review should possibly look beyond just the local market when considering potential competitive effects. This implication is in line with takeaways from other recent work on out-of-market hospital mergers by Lewis and Pflum (2014) and Dafny et al. (2015), who also find meaningful effects from out-of-market mergers.

One weakness of my analysis is direct evidence of the underlying mechanism(s) through which multimarket contact softens hospital competition. The theoretical literature demonstrates that multimarket contact can facilitate tacit collusion under many circumstances, but

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

[25]Note that my estimates are limited to the prices paid to hospitals by private insurers. How much consumers are affected ultimately 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 (2015) 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 available. Such estimates would be useful to provide a more complete interpretation of the effects of forces such as multimarket contact that may impact hospital prices.

[26]For a list of these mergers, 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. For instance, Community Health Systems divested two hospitals in order to receive approval from the FTC to complete the transaction.

I have not been able to devise straightforward tests for 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 litigations may make the inner workings of negotiations available for study, at least on a case-by-case basis.[28]

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8 Appendix

8.1 Figures and Tables

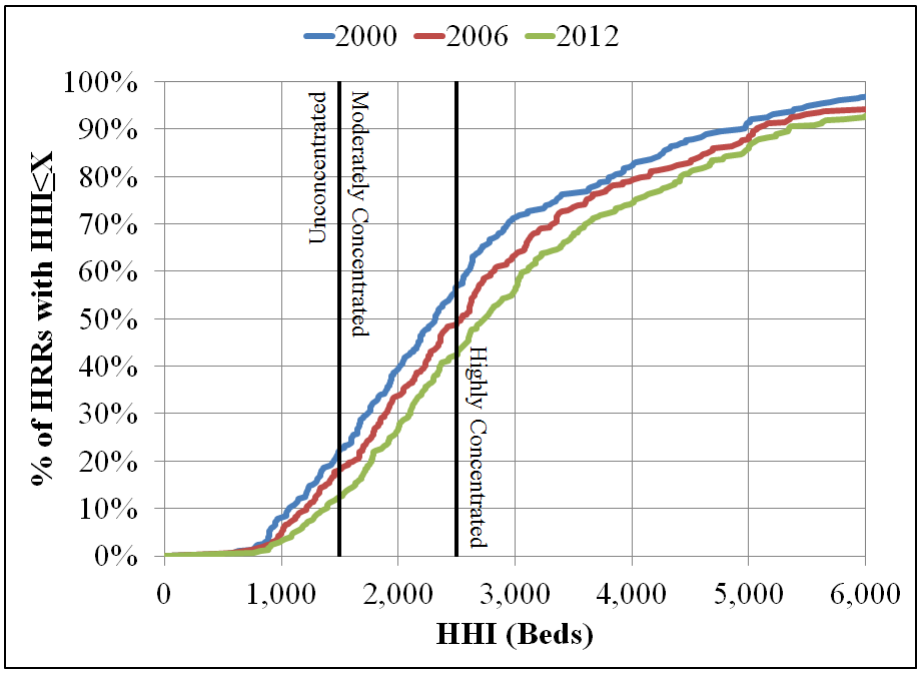


Figure 2: CDF of HHI Across HRRs by Year The figure is censored from the right at HHI=6,000. 3%, 6%, and 7% of HRRs have HHI>6,000 in 2000, 2006, and 2012 (respectively).

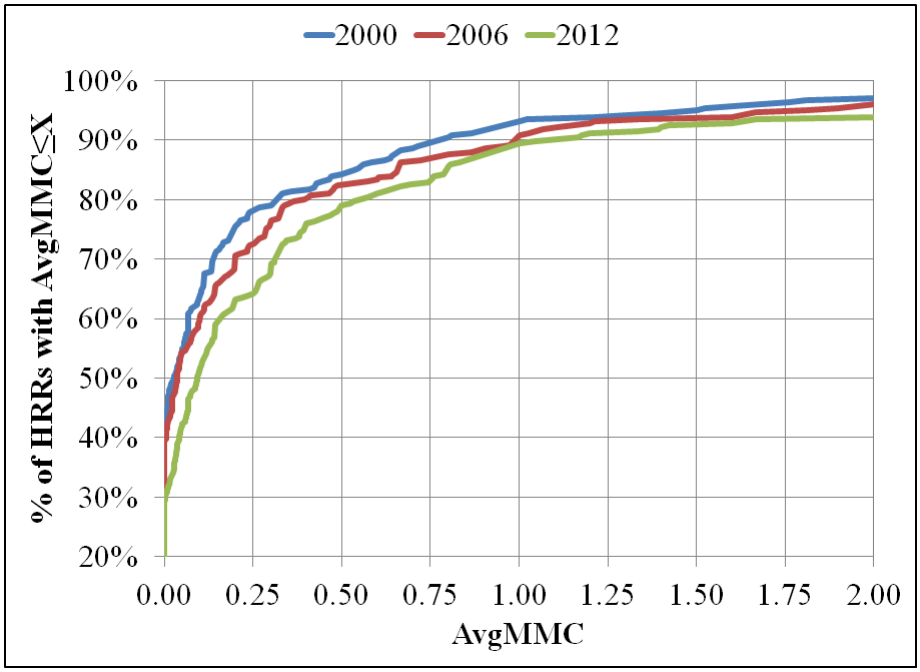
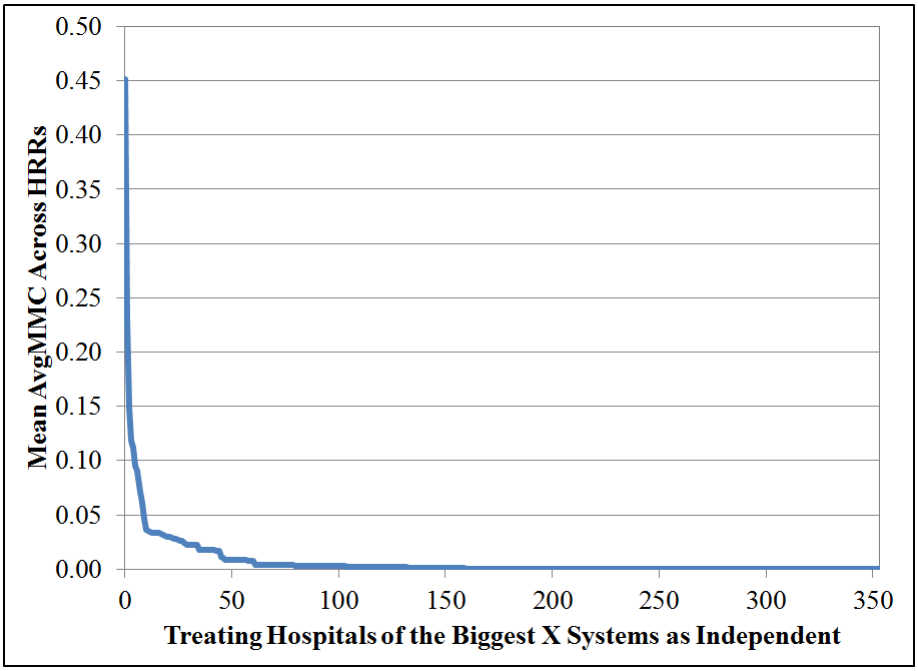


Figure 3: CDF of $AvgMMC$ Across HRRs by Year The figure is censored from the right at $AvgMMC = 2$. 3%, 4%, and 6% of HRRs have $AvgMMC > 2$ in 2000, 2006, and 2012 (respectively).



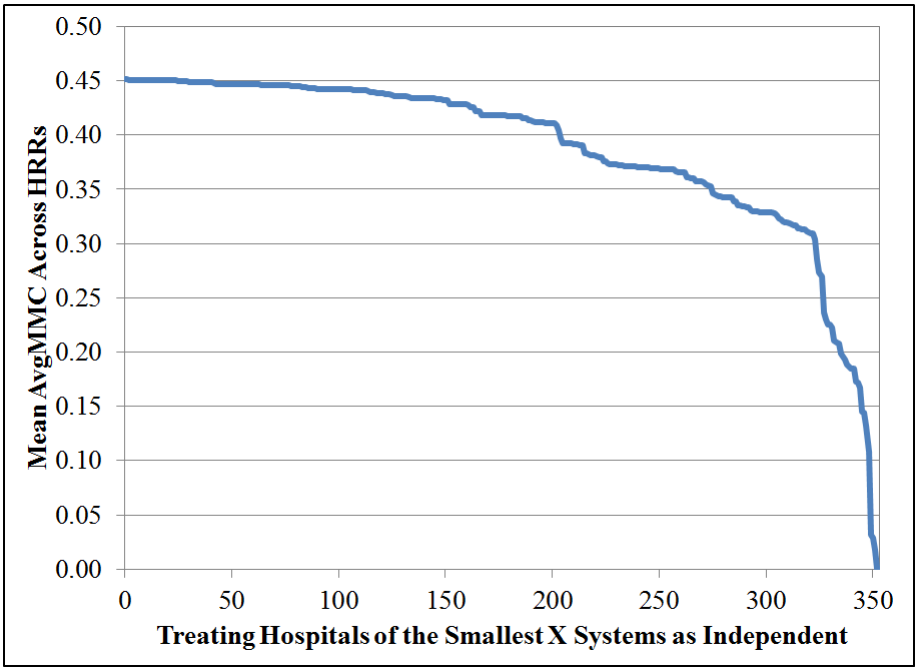


Figure 4: MMC Statistics After Dissolving Hospital Systems, 2012 "Biggest" and "smallest" are in terms of hospitals owned, breaking ties by total hospital beds. In the top panel, I successively replace hospital systems – going from the biggest to the smallest systems – as collections of independent hospitals and then recalculate the mean of $AvgMMC$ across HRRs. In the bottom panel, I do the same but going from the smallest to the biggest systems.

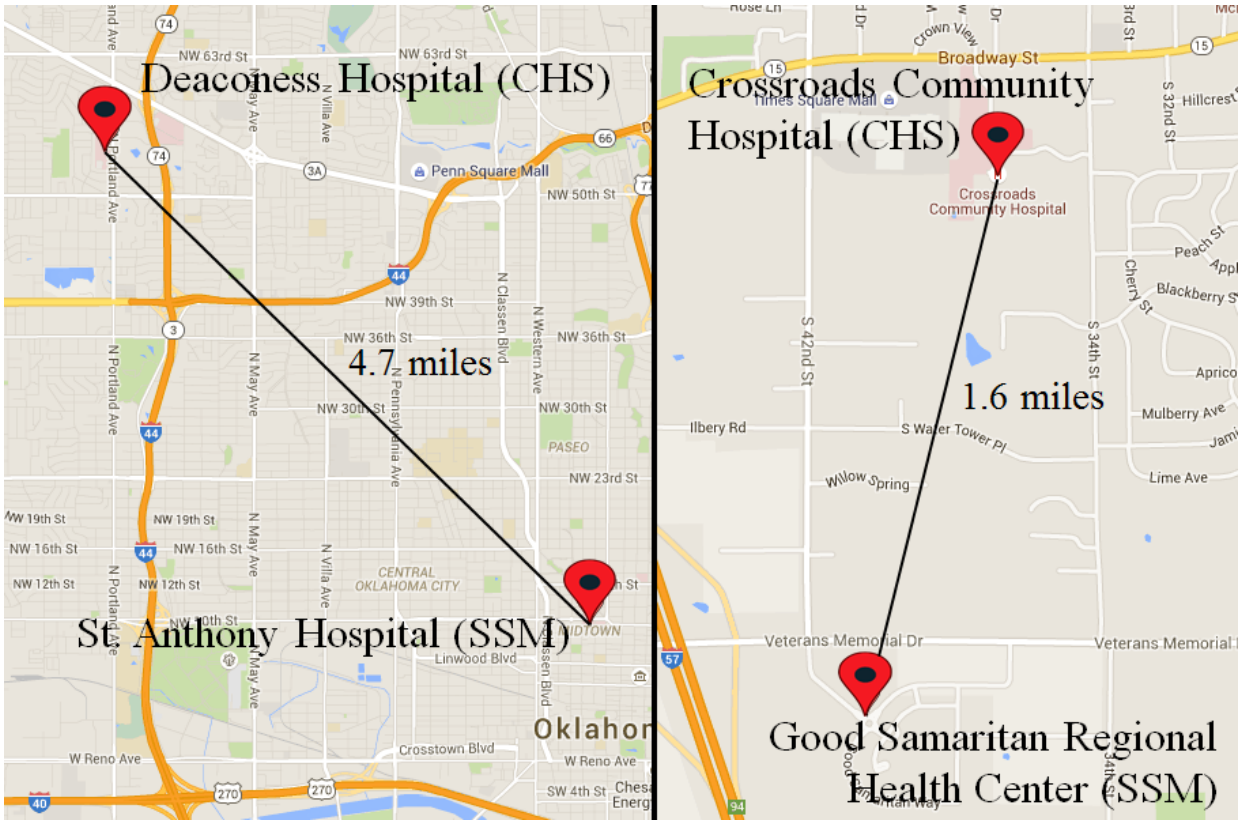


Figure 5: Example of Out-of-Market M&A and Multimarket Contact The left panel is Oklahoma City, OK and the right panel is Mount Vernon, IL. In 2006, Community Health Systems (CHS) acquired Deaconess Hospital in Oklahoma City, less than 5 miles from SSM Health's (SSM) St. Anthony Hospital. At the same time, both systems owned hospitals within 2 miles of each other in Mount Vernon, IL. CHS' acquisition of Deaconess therefore triggered an increase in multimarket contact between CHS and SSM.

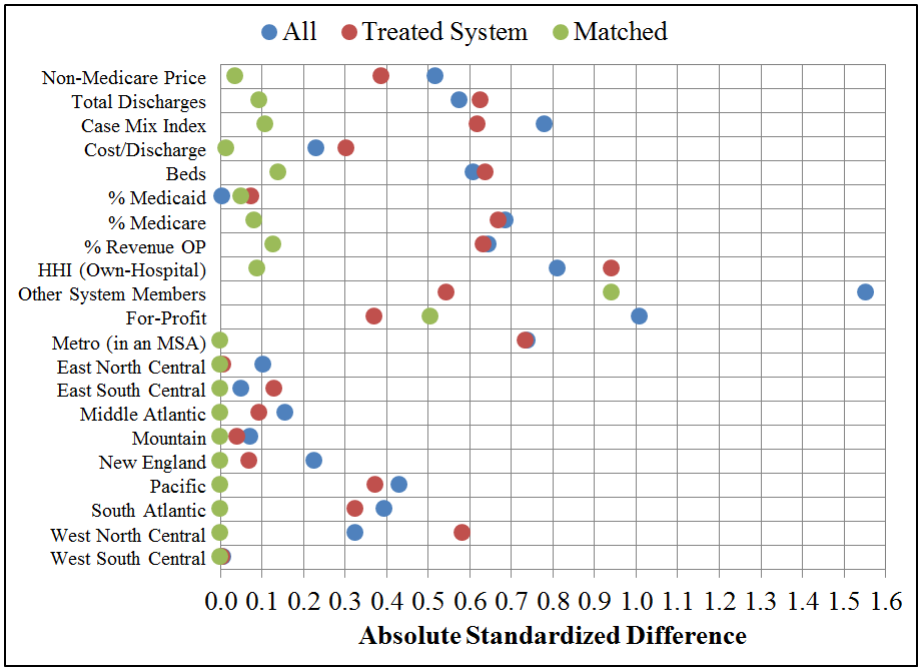


Figure 6: Absolute Standardized Differences Between Treatment and Control Hospitals For the matched control group, I match exactly on metro status and Census division so those differences are reduced to zero by construction.

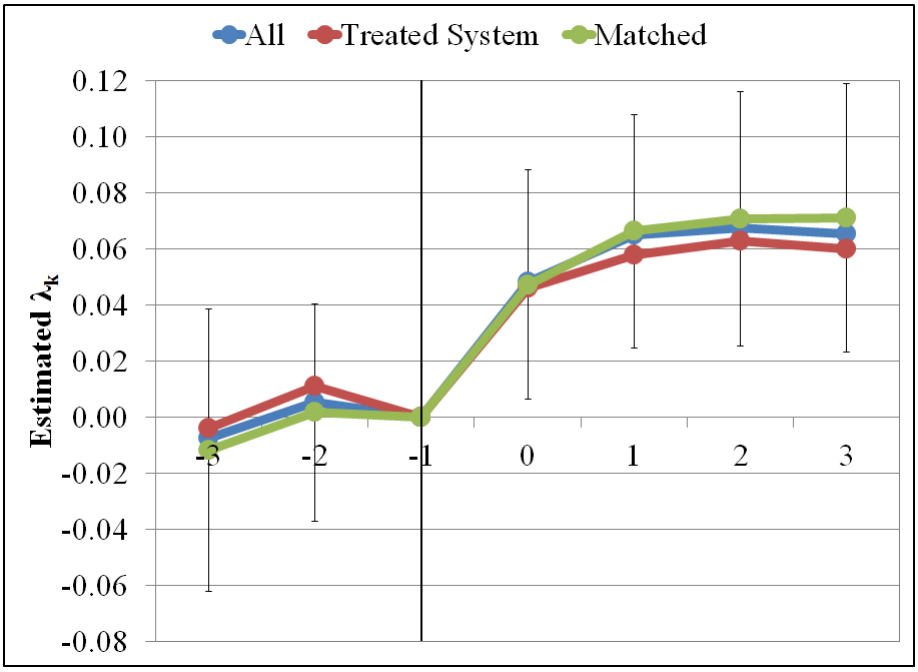


Figure 7: Leads & Lags Results The figure plots the estimated λ_k coefficients from equation (5) with $X_{hjt} = \mathbf{0}$, observations weighted by total discharges, and standard errors clustered by hospital. The year before treatment, $k = -1$, is the omitted category. 95% confidence intervals are plotted for the matched controls specification.

Table 1: Market Summary Statistics, 2010

Market Definition:	HRR (multi-owner)		HSA (multi-owner)		HSA (all)	
Markets:	305		455		3,174	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Hospitals	14.3	12.9	3.5	3.0	1.4	1.4
Hospital Owners	10.1	8.4	2.9	1.9	1.3	1.0
Hospitals per Owner	1.43	0.47	1.16	0.33	1.04	0.18
Total Discharges	105,161	117,971	43,721	52,386	10,178	24,941
Total Beds	2,148	2,301	875	1,029	208	489
% For-Profit	0.165	0.192	0.228	0.284	0.147	0.334
AvgMMC	0.405	0.911	0.316	0.824	–	–
HHI (Beds)	3,064	1,715	5,340	1,721	9,328	1,762

Notes: All numbers are from 2010. Only a single HRR has one owner in 2010. Discharges and beds are sums over all hospitals in the market. $AvgMMC$ is undefined for markets with only one owner.

Table 2: Traditional MMC Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Market Definition:		HRR			HSA	
AvgMMC	**0.022****	**0.022****	**0.022****	**0.020*****	**0.019*****	**0.018*****
	(0.008)	**(0.009)**	**(0.011)**	**(0.005)**	**(0.005)**	**(0.005)**
ln(CMI)	0.121**	0.122**	0.114**	0.163**	0.163**	0.155**
	(0.052)	(0.051)	(0.051)	(0.064)	(0.064)	(0.062)
ln(Cost/Discharge)	0.913***	0.913***	0.920***	0.871***	0.871***	0.876***
	(0.031)	(0.031)	(0.032)	(0.037)	(0.037)	(0.035)
ln(Beds)	0.028***	0.028***	0.026***	0.060***	0.060***	0.055***
	(0.009)	(0.009)	(0.008)	(0.015)	(0.015)	(0.012)
% Medicaid	-0.596***	-0.596***	-0.604***	-0.592***	-0.592***	-0.606***
	(0.106)	(0.106)	(0.098)	(0.141)	(0.141)	(0.129)
% Revenue OP	-0.276**	-0.277**	-0.296***	-0.293**	-0.294**	-0.356***
	(0.105)	(0.105)	(0.095)	(0.112)	(0.112)	(0.102)
For-Profit	0.171***	0.171***	0.068***	0.155***	0.155***	0.084**
	(0.021)	(0.021)	(0.023)	(0.024)	(0.024)	(0.032)
HHI (Beds)		0.122	0.093		0.068	0.031
		(0.098)	(0.092)		(0.081)	(0.077)
ln(System Span)		0.002	-0.014		0.003	-0.011
		(0.013)	(0.012)		(0.009)	(0.010)
Year FE	✓	✓	✓	✓	✓	✓
Market FE	✓	✓	✓	✓	✓	✓
System-Year FE^{+}			✓			✓
Markets	306	306	306	510	510	510
Hospitals	4,414	4,414	4,414	1,763	1,763	1,763
Observations	37,176	37,176	37,176	15,339	15,339	15,339
R-squared	0.710	0.710	0.727	0.722	0.722	0.748

Notes: ***p<0.01, **p<0.05, *p<0.10. Observations are weighted by total discharges and standard errors are clustered by state. $^{+}$includes system cross year fixed effects for the biggest 20 systems, defined in terms of average hospitals owned per year over the period.

Table 3: Own and Competitor Multimarket Contact

	(1)	(2)	(3)	(4)	(5)	(6)
Market Definition:		HRR			HSA	
OwnAvgMMC	**0.054*** **	**0.054*** **	**0.035*** **	**0.079** **	**0.082** **	**0.096** **
	(0.010)	**(0.010)**	**(0.012)**	**(0.035)**	**(0.035)**	**(0.038)**
OthAvgMMC	**0.006**	**0.006**	**0.007**	**-0.010**	**-0.008**	**0.003**
	(0.010)	**(0.010)**	**(0.010)**	**(0.016)**	**(0.015)**	**(0.014)**
ln(CMI)	0.127**	0.127**	0.120**	0.204**	0.204**	0.207**
	(0.054)	(0.054)	(0.052)	(0.094)	(0.094)	(0.089)
ln(Cost/Discharge)	0.916***	0.916***	0.920***	0.853***	0.853***	0.851***
	(0.032)	(0.032)	(0.032)	(0.047)	(0.047)	(0.048)
ln(Beds)	0.027***	0.027***	0.026***	0.057***	0.057***	0.057***
	(0.009)	(0.009)	(0.008)	(0.018)	(0.018)	(0.014)
% Medicaid	-0.572***	-0.572***	-0.597***	-0.572***	-0.571***	-0.612***
	(0.101)	(0.101)	(0.097)	(0.154)	(0.154)	(0.144)
% Revenue OP	-0.256**	-0.256**	-0.288***	-0.321**	-0.321**	-0.400***
	(0.104)	(0.104)	(0.097)	(0.127)	(0.128)	(0.106)
For-Profit	0.119***	0.119***	0.066***	0.124***	0.124***	0.110***
	(0.015)	(0.015)	(0.022)	(0.025)	(0.025)	(0.036)
HHI (Beds)		0.135	0.100		0.076	0.044
		(0.132)	(0.125)		(0.143)	(0.156)
ln(System Span)		-0.003	-0.011		-0.021	-0.037*
		(0.014)	(0.014)		(0.017)	(0.020)
Year FE	✓	✓	✓	✓	✓	✓
Market FE	✓	✓	✓	✓	✓	✓
System-Year FE^{+}			✓			✓
Markets	297	297	297	199	199	199
Hospitals	4,385	4,385	4,385	1,133	1,133	1,133
Observations	36,752	36,752	36,752	9,448	9,448	9,448
R-squared	0.712	0.712	0.727	0.696	0.696	0.732

Notes: ***p<0.01, **p<0.05, *p<0.10. Observations are weighted by total discharges and standard errors are clustered by state. $^{+}$includes system cross year fixed effects for the biggest 20 systems, defined in terms of average hospitals owned per year over the period.

Table 4: Comparing Treatment and Control Hospitals

		Control Group		
	Treated	All	Treated System	Matched
Hospitals	347	3,047	405	347
Price	$7,846	$6,213	$6,619	$7,728
Total Discharges	10,702	6,004	5,585	9,936
Case Mix Index	1.45	1.25	1.29	1.42
Cost/Discharge	$8,155	$7,445	$7,219	$8,203
Beds	244.7	144.3	139.8	221.6
% Medicaid	0.134	0.133	0.126	0.128
% Medicare	0.349	0.457	0.454	0.362
% Revenue OP	0.354	0.449	0.447	0.373
HHI (Own-Hospital)	2,771	5,345	5,757	3,057
Other System Members (mean)	65.0	7.1	44.7	29.9
Other System Members (median)	27	0	21	3
For-Profit	0.415	0.087	0.294	0.251
Metro (in an MSA)	0.882	0.514	0.516	0.882
Census Division				
East North Central	0.124	0.162	0.121	0.124
East South Central	0.066	0.080	0.101	0.066
Middle Atlantic	0.055	0.101	0.027	0.055
Mountain	0.061	0.080	0.072	0.061
New England	0.003	0.050	0.017	0.003
Pacific	0.233	0.098	0.116	0.233
South Atlantic	0.280	0.138	0.163	0.280
West North Central	0.043	0.159	0.249	0.043
West South Central	0.135	0.133	0.133	0.135

Notes: All statistics are measured in the first year that a hospital appears in the data – 1998 for 94% of hospitals. Price and cost per discharge are measured in 2010 dollars.

Table 5: Difference-in-Differences MMC Regressions

Panel A: Post Only (Equation (4))

	(1)	(2)	(3)
Control Group:	All	Treated System	Matched
$t \geq \tau_h$	0.061***	0.053***	0.066***
	(0.014)	(0.016)	(0.015)
Year FE	✓	✓	✓
Hospital FE	✓	✓	✓
Hospitals	3,394	752	694
Observations	33,997	6,324	6,308
R-squared (within)	0.172	0.183	0.164

Panel B: Leads & Lags (Equation (5))

	(1)	(2)	(3)
Control Group:	All	Treated System	Matched
$t = \tau_h - 3$	-0.007	-0.004	-0.012
	(0.025)	(0.026)	(0.026)
$t = \tau_h - 2$	0.005	0.011	0.002
	(0.019)	(0.020)	(0.020)
$t = \tau_h - 1$	0	0	0
	–	–	–
$t = \tau_h$	0.048**	0.046**	0.047**
	(0.020)	(0.021)	(0.021)
$t = \tau_h + 1$	0.065***	0.058***	0.066***
	(0.020)	(0.022)	(0.021)
$t = \tau_h + 2$	0.068***	0.063***	0.071***
	(0.022)	(0.024)	(0.023)
$t = \tau_h + 3$	0.065***	0.060**	0.071***
	(0.023)	(0.025)	(0.024)
Year FE	✓	✓	✓
Hospital FE	✓	✓	✓
Hospitals	3,394	752	694
Observations	33,997	6,324	6,308
R-squared (within)	0.172	0.183	0.164

Notes: ***p<0.01, **p<0.05, *p<0.10. Observations are weighted by total discharges and standard errors are clustered by hospital. In Panel B, $t = \tau_h - 1$ is the omitted category.

Table 6: Own and Competitor Multimarket Contact: Instrumental Variables

	(1)	(2)	(3)	(4)	(5)	(6)
Market Definition:		HRR			HSA	
OwnAvgMMC	**0.109****	**0.109****	**0.195****	**0.218**	**0.222***	**0.285****
	(0.054)	**(0.054)**	**(0.084)**	**(0.133)**	**(0.134)**	**(0.121)**
OthAvgMMC	0.033	0.034	0.070*	0.054	0.058	0.080
	(0.031)	(0.031)	(0.040)	(0.065)	(0.066)	(0.051)
ln(CMI)	0.127**	0.128**	0.127**	0.206**	0.205**	0.209**
	(0.056)	(0.056)	(0.056)	(0.096)	(0.096)	(0.089)
ln(Cost/Discharge)	0.918***	0.918***	0.922***	0.857***	0.857***	0.853***
	(0.032)	(0.032)	(0.034)	(0.046)	(0.046)	(0.046)
ln(Beds)	0.026***	0.026***	0.025***	0.055***	0.055***	0.056***
	(0.009)	(0.009)	(0.008)	(0.019)	(0.019)	(0.014)
% Medicaid	-0.558***	-0.558***	-0.579***	-0.540***	-0.539***	-0.586***
	(0.095)	(0.095)	(0.095)	(0.134)	(0.135)	(0.125)
% Revenue OP	-0.243**	-0.243**	-0.276***	-0.309***	-0.309***	-0.397***
	(0.096)	(0.096)	(0.092)	(0.117)	(0.116)	(0.093)
For-Profit	0.073	0.073	0.051**	0.083*	0.084*	0.108***
	(0.045)	(0.045)	(0.021)	(0.049)	(0.048)	(0.031)
HHI (Beds)		0.150	0.135		0.026	-0.017
		(0.152)	(0.178)		(0.161)	(0.170)
ln(System Span)		-0.017	-0.029		-0.055*	-0.069***
		(0.021)	(0.019)		(0.029)	(0.026)
Year FE	✓	✓	✓	✓	✓	✓
Market FE	✓	✓	✓	✓	✓	✓
System-Year FE$^+$			✓			✓
Markets	297	297	297	199	199	199
Hospitals	4,385	4,385	4,385	1,133	1,133	1,133
Observations	36,752	36,752	36,752	9,448	9,448	9,448
R-squared	0.709	0.709	0.710	0.688	0.688	0.720
First stage F-stat	27.59	28.07	17.76	42.46	44.24	24.95

Notes: ***p<0.01, **p<0.05, *p<0.10. All specifications instrument for $OwnAvgMMC_{ht}$ with $post_{ht}$ from the difference-in-differences analysis. Observations are weighted by total discharges and standard errors are clustered by state. $^+$includes system cross year fixed effects for the biggest 20 systems, defined in terms of average hospitals owned per year over the period.

Table 7: Difference-in-Differences MMC Regressions: Direct and Indirect Effects

Panel A: Post Only

	Direct	Indirect
$t \geq \tau_h$	0.060***	-0.011
	(0.014)	(0.014)
Year FE	✓	
Hospital FE	✓	
Hospitals	3,384	
Observations	32,575	
R-squared (within)	0.165	

Panel B: Leads & Lags

	Direct	Indirect
$t = \tau_h - 3$	-0.007	-0.003
	(0.025)	(0.021)
$t = \tau_h - 2$	0.006	0.039
	(0.019)	(0.026)
$t = \tau_h - 1$	0	0
	–	–
$t = \tau_h$	0.048**	0.016
	(0.020)	(0.016)
$t = \tau_h + 1$	0.064***	-0.019
	(0.020)	(0.031)
$t = \tau_h + 2$	0.067***	0.010
	(0.022)	(0.021)
$t = \tau_h + 3$	0.064***	-0.004
	(0.023)	(0.021)
Year FE	✓	
Hospital FE	✓	
Hospitals	3,384	
Observations	32,575	
R-squared (within)	0.165	

Notes: ***p<0.01, **p<0.05, *p<0.10. Observations are weighted by total discharges and standard errors are clustered by hospital. Each panel is a single regression, estimated using the all control group. In Panel B, $t = \tau_h - 1$ is the omitted category. "Direct" refers to hospitals experiencing an increase in multimarket contact between their owner and the owner of a hospital within 20 miles. "Indirect" refers to other hospitals in the immediate area (within 20 miles).

Table 8: Falsification Test: Medicare Prices

Panel A: (log) Medicare Price

	(1)	(2)	(3)
Control Group:	All	Treated System	Matched
$t \geq \tau_h$	-0.000	0.003	0.002
	(0.005)	(0.005)	(0.005)
Year FE	✓	✓	✓
Hospital FE	✓	✓	✓
Hospitals	3,394	752	694
Observations	34,299	6,387	6,368
R-squared (within)	0.250	0.193	0.246

Panel B: (log) Ratio of Non-Medicare to Medicare Price

	(1)	(2)	(3)
Control Group:	All	Treated System	Matched
$t \geq \tau_h$	0.061***	0.050***	0.063***
	(0.014)	(0.016)	(0.016)
Year FE	✓	✓	✓
Hospital FE	✓	✓	✓
Hospitals	3,394	752	694
Observations	33,997	6,324	6,308
R-squared (within)	0.085	0.117	0.094

Notes: ***p<0.01, **p<0.05, *p<0.10. Observations are weighted by total discharges and standard errors are clustered by hospital.

Table 9: Robustness Checks: Dafny, Ho, and Lee (2015)

Panel A: In-State vs. Out-of-State

	(1)	(2)	(3)
Control Group:	All	Treated System	Matched
$t \geq \tau_h$, In-State	0.061***	0.056***	0.063***
	(0.018)	(0.020)	(0.019)
$t \geq \tau_h$, Out-of-State	0.063***	0.048**	0.070***
	(0.020)	(0.020)	(0.020)
Year FE	✓	✓	✓
Hospital FE	✓	✓	✓
Hospitals	3,394	752	694
Observations	33,997	6,324	6,308
R-squared (within)	0.172	0.183	0.164

Panel B: Acquirer vs. Non-Acquirer

	(1)	(2)	(3)
Control Group:	All	Treated System	Matched
$t \geq \tau_h$, Acquirer	0.064***	0.058**	0.068***
	(0.023)	(0.025)	(0.024)
$t \geq \tau_h$, Non-Acquirer	0.059***	0.049***	0.064***
	(0.015)	(0.017)	(0.016)
Year FE	✓	✓	✓
Hospital FE	✓	✓	✓
Hospitals	3,394	752	694
Observations	33,997	6,324	6,308
R-squared (within)	0.172	0.183	0.164

Notes: ***p<0.01, **p<0.05, *p<0.10. Observations are weighted by total discharges and standard errors are clustered by hospital.

8.2 Optimal Matching

In the final sample, there are 347 treatment hospitals and 3,047 potential control hospitals. A match can therefore be described by a 1,057,309 (=347*3,047) 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. The goal of the matching is to find the "best" match that meets all relevant constraints. Formally, the matching problem is given by:

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

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

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

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

$$g(\boldsymbol{a}) \in \Omega \tag{6.4}$$

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. Constraint (6.4) – that the match meets some criteria beyond those captured by (6.1)-(6.3) – can in principle impose many different conditions on the match, such as balancing the distributions of covariates across the treatment and control groups.

For $d(t,c)$, I use the Mahalanobis distance with the following vector of covariates, each measured in the initial year of the data: non-Medicare price, total discharges, cost per discharge, total beds, % Medicaid, % Medicare, % gross revenue from outpatient activity, (own-hospital) HHI, and 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[29] differ by more than 0.2 standard deviations (the recommendation of Austin (2011b)). 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. I impose no additional constraints – such as measures of covariate balance, parallel price trends pre-treatment, etc. – on the match.

8.3 Difference-in-Differences Specification Tests

To evaluate the robustness of the difference-in-differences results presented in the text, I estimated a variety of specifications that change various aspects of the analysis. I performed ten different specification tests:

1. Add controls X_{hjt}: (log) case mix index, (log) cost per discharge, (log) beds, % Medicaid, % Revenue OP, for-profit status, own-hospital HHI, and (log) system size
   - In addition to the Medicare price falsification test, this specification checks that observed pricing effects are not likely due to concurrent changes in other factors affecting prices like service mix.
2. System by year fixed effects
   - I estimate this specification only using the treated system control group. By including system by year fixed effects, the impact of treatment is estimated only using within-system variation in price trends between treated and untreated hospitals.
3. Unweighted
   - This specification checks that the estimated effect is robust to eliminating the discharge weights.
4. Cluster the standard errors by state
   - In the main specification, standard errors are clustered by hospital. Clustering by state allows for correlation in the errors across hospitals within the state (a more conservative clustering approach).
5. Drop the three systems generating the most treatment hospitals

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

- About one-third of the 347 treatment hospitals in the main specification come from three systems. This specification checks whether the effect of multimarket contact persists after removing these three systems.

6. 15 mile in-market radius
   - This specification checks that the estimated effect is robust to a smaller definition of overlap (compared to 20 miles in the main specification).
7. 25 mile in-market radius
   - This specification checks that the estimated effect is robust to a larger definition of overlap (compared to 20 miles in the main specification).
8. Drop hospitals treated more than once
   - In the main specification, I set the year of treatment to be the first year in which a hospital is treated. About 40% of treatment hospitals are treated more than once. This specification limits the sample to the hospitals that are treated only a single time during the period.
9. Do not exclude acquired hospitals
   - In the main specification, I excluded hospitals acquired at any point during the period primarily to clearly distinguish the effect of multimarket contact from any system acquisition effects like those documented in Lewis and Pflum (2014). However, this restriction substantially reduces the number of hospitals in-sample, as nearly one-fourth of hospitals in the data change owners at some point during the period.
10. Drop hospitals that ever become critical access
    - Hospitals that become critical access have an undefined price after becoming critical access, and also may ndergo substantial operational changes prior to becoming critical access. Eliminating these hospitals from the sample ensures that any effects due to CAH conversions (e.g., on the composition of the sample over time) are unlikely to be generating the observed results.

The results are given in Table 10. In each cell of the table, I report the estimated coefficient on $post_{ht}$ for the modification listed in the first column, using the control group listed in the first row. Across all specifications, treatment is associated with a 3 to 7 percent increase in hospital prices. Only a single estimate (dropping the three systems contributing the most treatment hospitals, estimated using the treated system control group) is not significant at the 5% level: that estimate is significant at the 10% level.

Table 10: Difference-in-Differences Alternative Specifications

Control Group:	All	Treated System	Matched
Main Specification	0.061***	0.053***	0.066***
	(0.014)	(0.016)	(0.015)
Add Controls	0.040***	0.027**	0.057***
	(0.012)	(0.014)	(0.014)
Include System-Year Fixed Effects	–	0.067***	–
		(0.017)	
Unweighted	0.058***	0.038**	0.050***
	(0.014)	(0.016)	(0.016)
Cluster Standard Errors by State	0.061***	0.053***	0.066***
	(0.018)	(0.019)	(0.017)
Drop 3 Systems with Most Treatments	0.045**	0.039*	–
	(0.018)	(0.021)	
15 Mile Radius	0.050***	0.034**	–
	(0.015)	(0.017)	
25 Mile Radius	0.046***	0.033**	–
	(0.011)	(0.013)	
Drop Hospitals Treated Multiple Times	0.055***	0.052***	–
	(0.018)	(0.020)	
Include Acquired Hospitals	0.045***	0.037***	–
	(0.011)	(0.013)	
Drop CAH Hospitals	0.061***	0.062***	–
	(0.014)	(0.015)	

Notes: ***p<0.01, **p<0.05, *p<0.10. All specifications include hospital and year fixed effects. Except where noted, observations are weighted by total discharges and standard errors are clustered by hospital. Specifications changing the sample of treated hospitals are not estimated using a matched control group, since that would require re-matching which I judged to be unnecessary.

8.4 Data Appendix

8.4.1 Hospital prices (HCRIS)

$$\text{non-Medicare price} = \frac{\text{inpatient charges} \cdot \big(1 - \text{discount factor}\big) - \text{Medicare payments}}{\text{total inpatient discharges} - \text{Medicare discharges}} \tag{7}$$

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.

8.4.2 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.

8.4.3 Other data construction notes

Below I list several other elements of the data construction process not discussed in the text. Please feel free to contact me with any other questions.

- 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 (e.g., excluding hospitals Puerto Rico), 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 so eliminate outliers from the measure (Dafny (2009) and Lewis and Pflum (2014)). I winsorize prices at the 5th and 95th percentiles in order to avoid dropping observations – the reported results are robust to different percentile thresholds and dropping rather than winsorizing outliers.