Multimarket Contact in the Hospital Industry

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Online Appendix

1 Traditional analysis

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

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

$$\ln\left(\text{price}_{hjt}\right) = \theta_j + \gamma_t + \lambda \cdot MMC_{jt} + X_{hjt}\beta + \varepsilon_{hjt}\,, \tag{1}$$

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

Market definition

I estimate equation (1) using two common ad hoc market definitions that are typically thought to bound the "ideal" market definition. The first market definition, hospital referral region (HRR), splits the country into 306 distinct areas. HRRs are defined using data about where Medicare patients go to receive major cardiovascular surgery and neurosurgery. Each HRR contains at least one city where both types of major surgery are performed, and therefore tend to be somewhat large. In most cases, HRRs are likely larger than the ideal market definition in that they include more hospitals than the ideal market definition would include. The second market definition, hospital service area (HSA), splits the country into more than 3,000 distinct areas. HSAs are collections of zip codes in which Medicare beneficiaries living in those zip codes receive most of their hospital care from hospitals in that area. Since hospital care tends to be delivered locally, HSAs are far smaller than HRRs. In most cases, HSAs are likely smaller than the ideal market definition in that they include fewer hospitals than the ideal market definition would include.

Multimarket contact measures

I also examine several different multimarket contact measures. The first, $AvgMMC$, is as defined in the main text: the average number of market overlaps per pair of owners in a market. Notably, $AvgMMC$ assigns equal weight to all pairs of owners in a market.

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

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

Control variables

I utilize controls X_{hjt} similar to those used in the main text. To account for changes in the price measure driven by service and patient mix, I include (log) case mix index, the fraction of total discharges accounted for by Medicaid (% Medicaid), and (log) total beds. I include for-profit status and HHI (calculating shares using beds) to control for any contemporaneous changes in for-profit presence and/or market concentration. Last, while time-invariant differences between markets that attract large hospital systems are swept away by the market fixed effects, it may be that the hospitals of these systems and the markets containing them have different price trends than other hospitals and markets for reasons unrelated to multimarket contact.[1] I control for the presence of systems by adding the (log) discharge weighted average number of markets in which owners in a given market compete ("system span"). Intuitively, the idea behind adding the system span control is for identification to come specifically from markets where multimarket systems are not only present but also overlap with one another.

[1] 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.

Results

Table 1 presents the results, with Panel A using HSA as the market definition and Panel B using HRR. The number of observations is much lower with HSA as the market definition because the multimarket contact measures are only defined for markets with multiple hospital owners. While few HRRs have only a single owner, the majority of HSAs have only a single owner. In odd-numbered columns, I estimate the model only including market and year fixed effects. In even-numbered columns, I add the control variables. The bottom row of each panel multiplies the point estimate of the effect of multimarket contact to the interquartile range of each measure, capturing the estimated price effect of moving from the 25th percentile to the 75th percentile of each measure.

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

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

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

Table 1: Traditional MMC Regressions, 2000-2010

Panel A: HSA Market Definition

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

Panel B: HRR Market Definition

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

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

2 Main result robustness: hospitals treated only once

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

Panel A: Post Only

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

Panel B: Leads & Lags

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

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

3 Data construction

Hospital prices (HCRIS)

$$\text{non-Medicare price} = \frac{\text{inpatient charges} \cdot \big(1 - \text{discount factor}\big) - \text{Medicare payments}}{\text{total inpatient discharges} - \text{Medicare discharges}} \quad (2)$$

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

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

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

Combining American Hospital Association and Irving Levin data

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

Other data construction notes

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

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

4 Optimal matching

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

$$\min_{\boldsymbol{a}} \sum_{t=1}^{T} \sum_{c=1}^{C} a_{t,c} \cdot d(t,c) \quad s.t. \tag{3}$$

$$a_{t,c} \in \{0,1\} \quad \forall\, t,c \tag{3.1}$$

$$\sum_{c=1}^{C} a_{t,c} = k_1 \quad \forall\, t \tag{3.2}$$

$$\sum_{t=1}^{T} a_{t,c} \leq k_2 \quad \forall\, c \tag{3.3}$$

t indexes treatments and c indexes controls. $d(t,c)$ is a function that maps treatment-control pairings to a non-negative real number (the distance between the pair). The objective of (3) 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 (3.1) imposes that each element of $\boldsymbol{a}$ is either 0 (unmatched) or 1 (matched) (binary integer constraints). Constraint (3.2) imposes that each treatment should be matched to k_1 controls. Constraint (3.3) imposes that each control should be matched to at most k_2 treatments.

For $d(t,c)$, I use the Mahalanobis distance with the following vector of covariates, each measured in 1998: non-Medicare price, total discharges, case mix index, % Medicaid, total beds, (own-hospital) HHI, and a count of other system members. I replace the Mahalanobis distance with a large number (larger than the maximum observed Mahalanobis distance) if the logit of the estimated propensity scores[3] differs by more than 0.2 standard deviations (the recommendation of Austin (2011)). I also require that the control hospital shares the same Metro status as the treatment and is in the same Census division. I set $k_1 = k_2 = 1$, so that each treatment is matched to a single control and each control is not permitted to be matched to more than one treatment.

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

References

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