Mergers and Marginal Costs: New Evidence on Hospital Buyer Power

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Abstract

We estimate the effects of horizontal mergers on marginal cost efficiencies – a ubiquitous merger justification – using data containing supply purchase orders from a large sample of US hospitals 2009-2015. The data provide a level of detail that has been difficult to observe previously, and a variety of product categories that allows us to examine economic mechanisms underlying "buyer power." We find that merger target hospitals save on average $176 thousand (or 1.5 percent) annually, driven by geographically local efficiencies in price negotiations for high-tech "physician preference items." We find only mixed evidence on savings by acquirers.

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1 Introduction

In the last several decades, hospital systems have consolidated substantially through horizontal mergers (Cutler and Scott Morton 2013; Gaynor and Town 2012). Researchers and regulators have raised concerns about these mergers' potential negative welfare effects due to increased concentration, and hospital mergers are heavily represented in Federal Trade Commission investigations (Dafny 2014; Coate 2018). A typical justification for these (and many other) horizontal mergers is their potential to generate efficiencies, leading to lower prices, improved quality, enhanced service, and/or new product introductions, with a particular emphasis on price (U.S. Department of Justice and the Federal Trade Commission 2010). A necessary, though not sufficient, condition for mergers to lower prices is that they first lower marginal costs. In this paper, we estimate the effects of hospital mergers on marginal costs, and investigate underlying "buyer power" mechanisms (e.g., buyer size and its interaction with buyer preferences as in Chipty and Snyder (1999)), using rich new data containing hospital supply purchase orders issued by a large sample of US hospitals 2009-2015.

Hospital supplies and devices accounted for a quarter of the growth in inpatient hospital spending between 2001 and 2006 (Maeda et al. 2012). The product markets in our data account for 23 percent of hospital operating costs (34 percent, excluding labor). Thus, savings on supply input costs represent perhaps the largest potential merger efficiency that is unambiguously *marginal*.[1] In calculating these efficiencies, merging parties typically cite the wide variation in prices paid across hospitals and argue that the merged entity will be able to obtain discounts. This variation is indeed large, with a Gini coefficient of 0.08 (or a coefficient of variation of 0.26) for the average category, across hospitals for the same exact brand-month.[2]

Our approach builds on recent work that estimates the effects of mergers on overall hospital costs (Dranove and Lindrooth 2003; Harrison 2010; Schmitt 2017). Combining the purchase order data with a database of hospital mergers, we estimate difference-in-differences models that compare cost trends at target and acquirer hospitals to control hospitals.

We find that the average merger target in our sample can expect to save 1.5 percent or \$176 thousand dollars per year (95 percent confidence interval [\$43,201, \$309,325]) on

[1] When labor costs are cited as merger efficiencies, they are often either administrative in nature or due to the shifting of services across facilities; the former is arguably less "marginal", while the latter may involve a quality tradeoff (Noether and May 2017).

[2] This price variation has been found to be driven by heterogeneity in hospital preferences and bargaining ability (Grennan 2013, 2014), and by variation in information and contracting frictions (Grennan and Swanson 2018a,b). The Gini coefficient is one half of the mean absolute difference between any randomly selected pair of hospitals, which is precisely the expected savings calculation merging hospitals might perform, as input prices are not typically shared during pre-merger due diligence.

costs for 47 top supply categories, while the average acquirer can expect to pay $302 dollars more (confidence interval [$-73,459, $73,515]). Taking the Gini coefficients as one measure of potential savings, these translate into targets saving 10 percent ([2.6,18.6]) of the amount that might be claimed in a merger justification, and acquirers saving 0 percent ([-4.5,4.5]).

In addition to being interesting in their own right, mergers also provide useful variation to examine economic mechanisms underlying "buyer power" at a scale beyond individual case studies, as they represent a shock to hospital system size that is plausibly uncorrelated with trends in any particular supply market.[3] Much like in markets for hospital services, prices in hospital input markets are typically determined via bilateral negotiations. In such an environment, the effects of mergers can be complex, depending on how they impact market structure and bargaining abilities (Grennan 2013; Gowrisankaran et al. 2015; Lewis and Pflum 2015; Dafny et al. 2017). Further, market power in upstream supply markets may decrease prices, but market power in downstream services markets may lead to higher downstream prices, and that greater overall pie may be "shared" with suppliers (Ho and Lee 2017).

In all of our analyses, we consider whether cost reductions (if any) are achieved through lower negotiated prices, cost-reducing shifts in utilization, or both. In our analysis of utilization patterns, we pay particular attention to the role of "standardization".[4] While standard Nash-in-Nash models of bargaining would predict lower prices for hospitals with larger consideration sets, recent research has found that restrictive networks of health care providers (Ho and Lee 2018, Gruber and McKnight 2016), restrictive drug formularies (Duggan and Scott Morton 2010), and restrictive pharmacy networks (Starc and Swanson 2018) can lead to lower costs for insurers. Similarly, hospitals argue that standardization of medical supply purchasing results in large savings (Noether and May 2017). We also explore heterogeneity in our reduced form merger treatment effects in order to speak to underlying mechanisms via which marginal costs might be impacted (see Section 3.1).

We find that target hospital savings are driven by a 2.6 percent decrease in costs for physician preference items (PPIs): expensive implantable devices over which physicians typically have strong brand preferences. This effect is entirely explained by targets negotiating lower prices within-brand, rather than changes in usage patterns, and is largest for small, local mergers (5.3-6.3 percent). In contrast, acquirers' 6.4 percent savings on inexpensive

[3]The product markets we consider vary in several dimensions that are likely to affect bargaining or to mediate the effects of mergers: these include supplier concentration, the strength of brand preferences based on perceived heterogeneity in quality, and the relative importance of contracting intermediaries.

[4]Throughout this paper, we follow industry terminology and use the term "standardization" to refer to hospitals' use of restrictive supply sets; e.g., use of one brand of implant for most joint replacement procedures.

commodities (which are largest for cross-market mergers) are more than counterbalanced by a small 1.1 percent increase in PPI costs post-merger. We find no significant evidence that savings are mediated by supplier concentration, downstream market power, or standardization. This set of patterns is nuanced, but consistent with: (1) buyer power driven by returns to scale that are more local in PPIs and national in commodities; and (2) fixed adjustment or renegotiation costs (Grennan and Swanson 2018b) making cost savings in commodities more beneficial for large acquirer systems.

2 Data and Setting

2.1 Hospital Purchasing Data

The primary data used in this study come from a unique database of all supply purchases made by over 1,200 US hospitals during the period 2009-2015. The data are from the PriceGuide™ benchmarking service (hereafter, "PriceGuide data") offered by the ECRI Institute, a non-profit health care research organization. For each transaction, we observe price, quantity, transaction month, and supplier.

Our analyses consider price negotiations between hospitals and suppliers for a large number of important product categories. Included products are among the top 50 product categories by *either* total spending *or* transactions. There are 71 such "top" categories total, but once we omit product categories that are too broad or with missing or inconsistent data, 47 remain.[5]

2.2 Hospital and Merger Data

To perform the analysis in the current study, we obtained permission to contract a trusted third-party to match facilities in the PriceGuide data to outside data from the Centers for Medicare and Medicaid Services (CMS), the American Hospital Association, and a merger roster. The third-party then provided us with access to the merged data for analysis, with hospital-identifiable information removed.

We obtained merger data from Cooper et al. (2015), which contain nearly all hospital

[5]See Grennan and Swanson (2018b) and Appendix B for details. Note that we use the term "brand" to refer to the "product" level at which prices are negotiated; e.g., Medtronic Resolute Integrity drug-eluting coronary stent. We use "product category" to refer to the "Universal Medical Device Nomenclature System (UMDNS) code" grouping included in the transaction files. The UMDNS system classifies devices by intended purpose and mechanism of action (e.g. drug-eluting coronary stents have UMDNS code 20383). Finally, we use "product class" to refer to each product's FDA risk class I-III, which closely align with commodities (class I), physician preference items (class III), and other medical/surgical products (class II).

mergers from 2000-2014. The data were generated by correcting known problems in the AHA: errors in timing of mergers due to lagged survey response; and erroneous combination of multiple facilities into single observations post-merger. These data were cross-checked against data from Schmitt (2017) and several business intelligence databases: Irving Levin Associates, Factset, and SDC Platinum. For more details on the merger data, see Appendix D of Cooper et al. (2015).

Each analytic sample includes facilities in the PriceGuide data that merged uniquely by name and location to general acute care hospitals in the AHA data. The PriceGuide data contain a large number (1,228) of hospitals; and the merger panel contains a large number of mergers over the same period (445 transactions impacting 661 targets and 1,753 acquirers). However, our data only include a given target/acquirer if the merged PriceGuide data contain at least one calendar year of pre-merger and post-merger data. Because the PriceGuide members join the database in a staggered fashion over time, this requirement reduces our sample to 33 targets and 98 acquirers taking part in 81 unique transactions, and 436 non-merging controls. This restriction is costly; however, our sample contains many merger case studies – whereas many analyses have considered single mergers in isolation (Kwoka 2015) – and the rich transaction-level cost information across 47 different product categories compensates in detail for this sample limitation.

Appendix B describes the effects of each merge on representativeness of our sample. Our sample covers larger hospitals, treating sicker patients, and more often in urban areas, than the population of AHA member hospitals. The PriceGuide mergers are also more likely to be non-profits and teaching hospitals, and tend to purchase in more categories.

2.3 Price Variation, by Product Class

For each of the products in our data, prices are determined in negotiation. The contracting environment is described further in Grennan and Swanson (2018b) and Appendix C. Negotiation can take place directly between a hospital administrator and a representative of the product's manufacturer, or hospitals may rely on group purchasing organizations (GPOs) to negotiate their contracts for many products.[6] Each product category is summarized in Table 1.

The bottom panel of Table 1 contains physician preference items. For PPIs, usage is driven by brand preferences of physicians, often surgeons, choosing which brand to use to treat a given patient. PPIs tend to be expensive cardiac and orthopedic surgical implants used in relatively advanced procedures and are not purchased by all hospitals: only 386

[6] GPO prices are typically used as a starting point for direct hospital-manufacturer negotiations for physician preference items and capital equipment (Schneller 2009).

Table 1: Summary of Product Categories

	% of $spend$	$\overline{spend}_{hy}$	N_{hjmy}	N_h	N_{tar}	N_{acq}	N_j	HHI_v	$\overline{q}_{ht}$	$\overline{p}_{hjmy}$	$CV_{h\|jmy}$	$Gini_{h\|jmy}$
Tags/Labels	0.0	875	76,498	530	30	74	498	0.22	2,921	32	0.44	0.11
Surgical Drapes	0.2	2,146	94,979	523	31	71	310	0.31	841	11	0.28	0.08
Needles	0.0	4,036	77,088	535	32	73	327	0.28	15,388	110	0.55	0.13
Dressings	0.4	5,555	150,422	543	33	79	557	0.26	6,773	20	0.33	0.09
IV Administration Kits	0.5	7,056	52,227	524	26	77	176	0.20	2,840	15	0.49	0.14
Drill Bits	0.4	7,104	235,142	509	26	72	335	0.26	51	189	0.22	0.08
Batteries	0.5	11,026	55,994	521	28	67	216	0.93	18,381	94	0.28	0.08
IVD Kits	4.4	34,367	489,850	541	33	80	1,429	0.39	54,868	229	0.39	0.12
Commodities: Total	6.5	69,029	1,235,570	553	33	84	3,849	.	98,863	144	0.37	0.11
Commodities: Average	0.8	9,021	154,025	528	30	74	481	0.36	12,758	87	0.37	0.10
Sutures Nylon Monofilament	0.1	1,111	45,931	524	29	77	201	0.25	325	8	0.27	0.06
Bone Wires	0.1	1,658	74,437	511	27	72	123	0.17	42	102	0.38	0.13
Angiography Cath.s	0.1	2,081	41,446	439	21	65	39	0.44	113	111	0.35	0.10
Tracheal Tubes	0.1	2,558	64,621	530	27	75	176	0.26	443	63	0.54	0.15
Sutures	0.3	3,071	46,029	532	30	77	260	0.22	341	112	0.41	0.10
Polypropylene Sutures	0.2	3,320	49,335	518	24	77	256	0.25	470	45	0.30	0.07
Trocars	0.3	4,942	65,531	520	26	73	188	0.16	141	76	0.31	0.09
Suture Anchors	0.4	6,327	52,957	503	24	71	61	0.41	19	381	0.19	0.07
GI Staples	0.5	7,033	18,185	488	18	62	32	0.25	50	238	0.54	0.18
Polymeric Mesh	0.5	8,867	93,376	528	32	75	385	0.17	16	977	0.20	0.06
Electrosurgical Forceps	0.6	9,076	42,604	492	22	63	93	0.10	28	905	0.40	0.12
Surgical Staplers	0.7	10,897	77,544	511	26	69	238	0.20	51	367	0.24	0.08
Bone Nails	0.5	10,938	53,259	480	23	65	123	0.29	8	1,558	0.19	0.07
Trauma Bone Plates	0.6	11,417	187,557	505	27	72	549	0.56	16	787	0.14	0.05
Bone Implant Putty	0.5	12,536	65,885	475	23	60	229	0.22	12	1,114	0.16	0.05
Spinal Bone Plates	0.5	13,881	48,428	382	16	43	234	0.18	9	1,709	0.26	0.08
Guiding Cath.	0.8	13,949	251,790	502	26	73	324	0.17	276	226	0.26	0.09
Guide Wires	1.0	17,878	352,437	523	30	77	423	0.13	317	122	0.26	0.09
Trauma Bone Screws	0.9	19,272	369,396	514	29	75	317	0.52	195	154	0.19	0.08
Bone Grafts	0.8	20,465	40,058	455	21	53	141	0.98	741	2,562	0.16	0.04
Aortic Stents	1.0	27,664	27,442	380	18	49	67	0.33	5	6,144	0.09	0.03
Ablation/Mapping Cath.s	0.8	28,121	64,080	329	13	41	107	0.27	28	1,188	0.18	0.07
Spinal Bone Screws	2.6	68,515	158,571	420	20	52	568	0.22	130	615	0.31	0.10
Other Med/Surg: Total	13.8	243,665	2,298,384	552	33	87	5,134	.	3,362	525	0.25	0.08
Other Med/Surg: Average	0.6	13,286	99,604	481	24	66	223	0.29	164	851	0.27	0.09
Intraocular Lenses	0.2	6,786	31,855	327	14	33	39	0.55	34	293	0.13	0.05
Spinal Rod Implants	0.2	7,170	60,302	365	16	43	265	0.18	18	444	0.32	0.09
Allografts	0.5	10,537	44,545	472	21	56	249	0.84	71	1,634	0.19	0.05
Embolization Coil	0.5	13,908	54,766	408	20	57	186	0.40	33	955	0.12	0.04
Mammary Prosth.	0.5	14,369	23,212	379	14	46	28	0.45	17	843	0.11	0.04
Acetabular Hip Prosth.	0.7	16,239	57,128	459	25	56	75	0.21	13	1,422	0.30	0.12
Spinal Stimulators	0.6	25,193	9,722	306	8	27	12	0.34	2	15,693	0.13	0.05
Tibial Knee Prosth.	1.2	27,858	101,896	467	25	60	206	0.19	23	1,371	0.23	0.08
Pacemakers	1.3	30,878	41,529	419	16	53	33	0.43	7	4,409	0.14	0.07
Femoral Hip Prosth.	1.3	31,404	144,116	471	25	60	437	0.21	20	1,767	0.30	0.10
Cardiac Valve Prosth.	0.7	31,703	16,842	254	11	42	10	0.40	6	5,752	0.15	0.07
Femoral Knee Prosth.	1.4	34,459	90,243	463	25	60	221	0.21	17	2,355	0.21	0.07
Spinal Spacers	1.4	43,020	69,580	370	16	39	486	0.14	14	3,524	0.22	0.06
Cardioverter Defib.	1.6	45,482	16,700	336	12	42	31	0.45	3	15,594	0.13	0.05
Resynchronization Defib.	1.7	49,308	11,314	324	12	38	10	0.47	2	20,897	0.12	0.05
Drug Eluting Stents	2.1	71,965	33,151	348	16	53	15	0.32	49	1,543	0.08	0.04
PPIs: Total	15.7	326,372	814,328	515	29	74	2,303	.	257	2,603	0.23	0.07
PPIs: Average	1.0	28,767	50,431	386	17	48	144	0.36	21	4,906	0.18	0.06

Notes: Summary statistics for main analysis sample. Authors' calculations from PriceGuide data. For each product category: "% of *spend*" is percent expenditure in entire PriceGuide database; $\overline{spend}_{hy}$ is average monthly spending; $N_{jhmy}, N_h, N_{tar}, N_{acq}$ and N_j are total number of observations, hospitals, target hospitals, acquirer hospitals, and brands; HHI_v is vendor Herfindahl-Hirschman Index (HHI); $\overline{q}_{hmy}$ is average monthly quantity; $\overline{p}_{hjmy}$ is average unit price; $CV_{h|jmy}$ is within-brand-month coefficient of variation across hospitals, averaged across all brand-months; $Gini_{h|jmy}$ is within-brand-month Gini coefficient of price, averaged over brand-months. "Total" rows contain aggregate statistics for all categories in each product class; unweighted average statistics across category-level analyses listed in the "Average" rows.

sample hospitals purchased the average PPI, and only 254 purchased "Cardiac Valve Prostheses." Purchasing hospitals spent $28,767 per month on the average PPI, due to PPIs' high prices.

The top panel of Table 1 contains commodities. Commodity products can be used in a hospital setting by hospital staff members with a variety of roles and scopes of practice. Conditional on a few characteristics, such as material, we do not expect particular manufacturers to be strongly preferred. Commodities tend to be the most commonly-purchased products in our data, purchased by 528 sample hospitals on average. They are markedly less expensive than PPIs: the average hospital spends only $9,021 per month on the average commodity.

The final product class considered is other medical and surgical items, shown in the middle panel of Table 1, which may have characteristics of both PPIs and commodities. They are used in moderately invasive procedures, but may or may not be associated with strong brand preferences. These products vary in popularity, and the unit price varies from $8 to $6,000. On average, hospitals spend $13,286 per month on product categories in this class.

The competitive landscape varies dramatically across these classes. There are many more brands to choose from in commodities (481) vs. PPIs (144). For PPIs, each brand is typically purchased directly from its manufacturer (there are 19 in the average category), and hospitals/systems tend to negotiate their own prices. In contrast, the average commodity is available from 77 vendors, brands produced by a particular manufacturer may be sold by multiple vendors, and hospitals are more likely to rely on GPO pricing (Schneller 2009). Despite these differences, all three classes are highly concentrated according to Horizontal Merger Guidelines, and there is a great deal of price dispersion: the average coefficient of variation is 0.37 in commodities and 0.18 in PPIs; and the Gini coefficient is 0.10 in commodities and 0.06 in PPIs.

3 Cost Implications of Mergers

3.1 Potential Mechanisms

Hospital leaders contend that mergers reduce costs through scale economies, reduced costs of capital, and clinical standardization (Noether and May 2017). Our rich cost data allow us to estimate the effects of mergers on "buyer power" in the form of scale economies in supplier negotiations, clinical standardization, and the interaction between the two.

The welfare effects of any merger efficiencies driven by input cost reductions will depend on the underlying mechanisms. In evaluating proposed mergers, the FTC and DOJ consider whether cost efficiencies are likely to be large, whether they are likely to pass through to consumers, and whether they are "likely to be accomplished with the proposed merger and unlikely to be accomplished in the absence of either the proposed merger or another means having comparable anticompetitive effects" (whether they are "merger-specific" (U.S. Department of Justice and the Federal Trade Commission 2010)). Thus, the agencies' consideration of efficiencies focuses for the most part on potential welfare gains in the downstream market.

Input cost efficiencies could also be welfare-neutral – a transfer between upstream and downstream firms – or themselves welfare-reducing. Hemphill and Rose (2018) distinguish cases where mergers increase monopsony power or bargaining leverage from cases where there are real resource savings, such as reduced waste. They conclude that the former cases reduce competition and should not be viewed by regulators as cognizable efficiencies.[7]

Hospital costs include substantial fixed and variable components. The variable portion of hospital costs scales with the number and severity of patients treated, the quantity of labor and "capital" inputs used per patient, and the prices of those inputs. The prices of inputs are, in turn, determined by brand choice and the price negotiated within each brand. Mergers may in theory impact any part of the hospital's cost function. However, fixed costs are unlikely to pass through to patients in the short run, changes in patient mix raise a battery of questions regarding agency and quality of care, and potential negative effects of monopsony power on labor costs are not rated kindly by antitrust authorities.[8] Thus, in this study, we focus on variable costs that are truly marginal in the sense that they are incurred along with performance of additional patient care – those costs most likely to impact downstream prices. Specifically, we examine whether mergers lead to economies of scale in variable supply costs due to changes in input choices and/or pricing.

An effect of mergers on efficient input choice might occur if, for example, a merger entails the hospitals adopting the management practices of the most efficient merging entity. Indeed, Bloom et al. (2014) find that larger hospitals have better management practices. The converse could also be true: mergers and acquisitions may spread practices that are detrimental to firms (Minemyer 2017) or consumers (Eliason et al. 2018).

Analyzing input pricing requires close attention to the details of hospital procurement. In hospital input markets, prices are determined via bilateral negotiations between suppliers and hospitals, perhaps with GPOs acting as proxy for groups of hospitals. For products

[7] One potential harm cited is dynamic inefficiency, in which upstream firms reduce investment and innovation due to increased downstream monopsony power.

[8] See discussion in Gaynor and Town (2012), regarding the DOJ's allegation of competitive harm in the purchase of physician services and temporary nursing services.

purchased through a GPO, we would predict a merger to impact purchasing if it moved the combined entity to a more favorable GPO membership tier, or if it induced a change in GPO and there is variation in purchasing across GPOs. For products whose prices are determined separately for each hospital/system, a larger merged entity might negotiate lower prices than either the target or acquirer would alone.

The effect of mergers on bilateral bargaining is ambiguous in the economics literature. When there is a monopoly supplier, larger firms may obtain better prices if the bargaining-surplus function is concave, in which case the supplier's surplus in bargaining with two independent firms is smaller at the margin than the average surplus in bargaining jointly with an integrated firm (Horn and Wolinsky 1988; Stole and Zwiebel 1996; Chipty and Snyder 1999; Inderst and Wey 2007). Further, larger buyer firms may spur competition among multiple suppliers (Snyder 1996, 1998; Dana 2012; Gans and King 2002; Marvel and Yang 2008). This improvement in integrated buyers' bargaining *position* may be reinforced by an increase in bargaining power (an improvement in the merged entity's disagreement point). In work on insurer-hospital bargaining, Lewis and Pflum (2015) find that bargaining power is a greater determinant of post-merger markups than bargaining position. Post-merger changes in bargaining *power* (the share of gains from trade obtained, conditional on bargaining positions) may be driven by various factors, including firm organizational structure, information, incentives, management, and leadership.

Finally, input choice and input pricing may interact. Dana (2012) posits that buyer groups' primary advantage results from their commitment to purchase from a single supplier in differentiated product markets. We see evidence of this in the hospital-insurer bargaining world: Sorensen (2003) shows that insurers' steering ability impacts pricing more than insurers' size; Gowrisankaran et al. (2015) model how insurers steer patients towards cheaper hospitals; and Ho and Lee (2018) note that restrictive hospital networks could reduce insurers' prices by up to 30 percent.

The evidence on these mechanisms suggests that mergers may impact input costs by reducing prices within brand, by encouraging efficient utilization of inputs, or both. We proceed by investigating the effects of mergers on brand-level prices, product category-level prices, and standardization. We estimate separate treatment effects for each product category and pooled treatment effects for PPIs, commodities, and other medical/surgical products. We then go further to investigate mechanisms.

3.2 Empirical Specifications

We estimate two reduced form price specifications. First, using a dataset containing unit prices for each product category (UMDNS code) u, hospital h, brand j, month m, year y, we estimate:

$$lnP_{uhjmy} = \alpha_u * \mathbb{1}[y = \tau_h] + \beta_u * \mathbb{1}[y > \tau_h] + \theta_h + \theta_{jmy} + \varepsilon_{uhjmy} \tag{1}$$

where τ_h is the year of hospital h's merger (if any), θ_h is a hospital fixed effect, and θ_{jmy} denotes brand-month-year fixed effects.[9] To avoid overweighting products purchased in small quantities, we weight each hospital-brand-year using the brand's expenditure share within the hospital-year. The month of merger is unknown, so we estimate separate treatment effects for the merger year (α_u) and the post-merger period (β_u).[10] We estimate separate regressions for acquirers and targets; the acquirers regression excludes targets, and vice versa. Intuitively, this regression examines the effect of mergers on negotiated prices *per unit* across all brands in a given category.

Next, using the same dataset, we estimate:

$$lnP_{uhjmy} = \alpha_u * \mathbb{1}[y = \tau_h] + \beta_u * \mathbb{1}[y > \tau_h] + \theta_{hj} + \theta_{jmy} + \varepsilon_{uhjmy} \tag{2}$$

where θ_{hj} denotes a set of hospital-brand fixed effects. This regression examines the average *within-brand* effect of mergers on negotiated prices, for brands purchased both before and after the merger. Comparing the results from specifications (1) and (2) tells us whether lower prices are achieved due to renegotiation vs. switching. In all regressions where the dependent variable is price, standard errors are clustered by hospital-brand.

In addition to the product category-specific regressions, we also estimate pooled regressions across all categories within each class. We stack all category-specific data within each class and estimate specifications (1) and (2), weighting by the expenditure share for each category within hospital-year, and allowing for hospital fixed effects θ_{uh} to vary by category u.[11]

In the left panel of Figure 1, we show the estimated coefficients β_u and corresponding 95 percent confidence intervals for specifications (1) and (2), for targets only. We observe several patterns of interest. First, each class has product categories with negative coefficients,

[9]Brand-specific time trends are necessary to control for the presence of brands both early and late in their life cycles in these data.

[10]In our baseline results, we report specifications where the post-merger period is a single year. We further restrict to mergers for which we have at least one year of pre- and post-merger data.

[11]We also estimate regressions using a clustered wild bootstrap for inference; the results in Table A8 are nearly identical to the main results in Table 2.

and product categories with positive coefficients, so that no clear visual pattern suggestive of cost efficiencies for target hospitals emerges. Second, the within-brand (hollow) coefficients are not consistently scaled up or down relative to the across-brand (solid) coefficients. Third, within commodities (circles) and other medical/surgical products (triangles), very few product categories have significant price effects: exceptions include negative effects for bone nails and trauma bone plates, and positive effects for monofilament sutures and spinal bone plates. Finally, there are a number of negative and significant price effects for important PPIs (squares) – defibrillators, pacemakers, and prostheses – but only one significant positive coefficient, for spinal spacers.

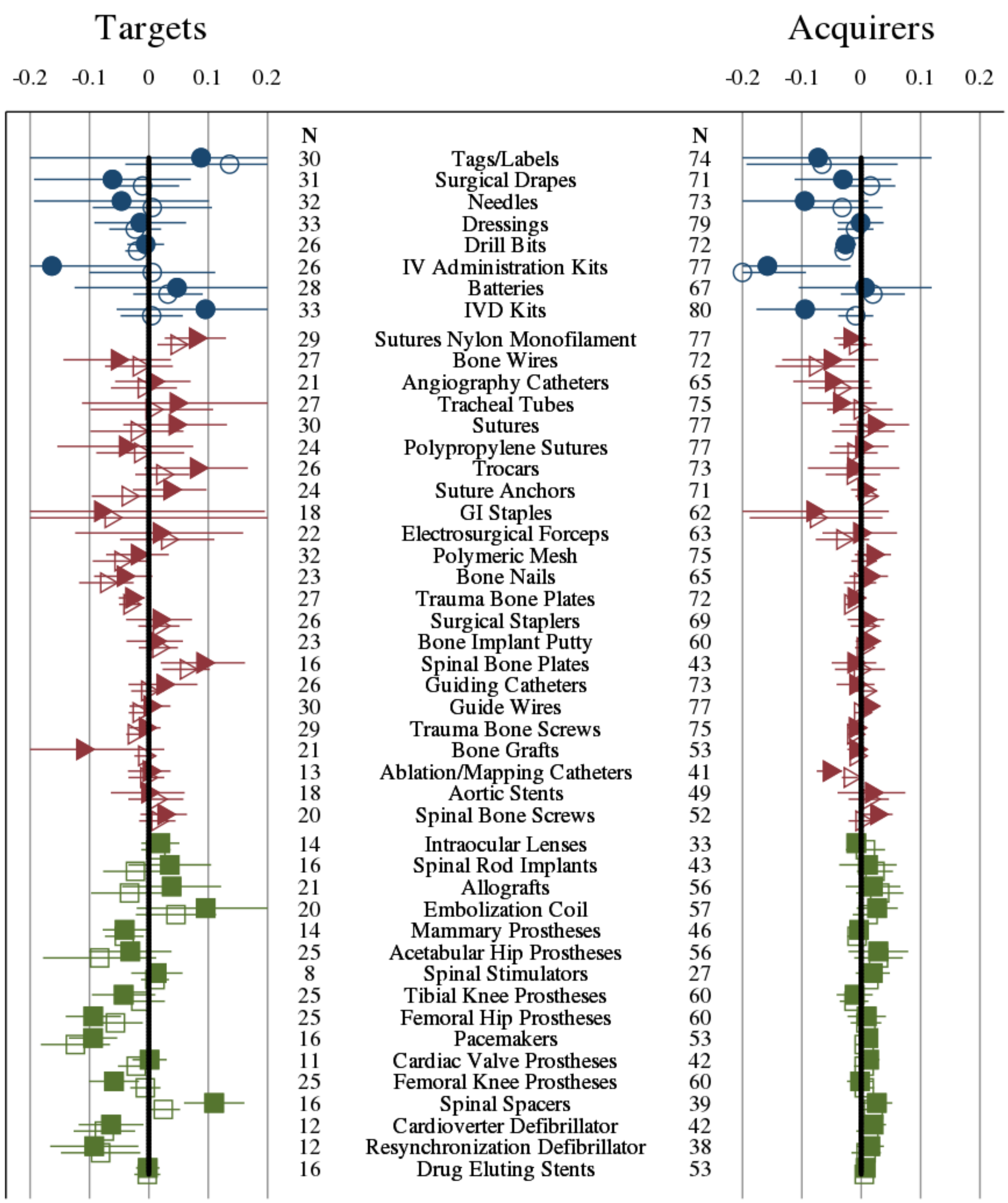
The left columns in the top panel of Table 2 show pooled coefficient estimates for each specification and class. These results indicate that, on balance, targets exhibit insignificant price *increases* in commodities or other medical/surgical products post-merger. However, they save a significant 2.6 percent on PPIs – the negative price effects documented above were in high-dollar categories (cardiac devices and prostheses) and more than offset the few positive effects in categories like spinal spacers and embolization coils. Finally, the within-brand coefficients are, if anything, slightly larger than the across-brand coefficients, indicating that all savings can be accounted for by renegotiations, rather than brand switching.

We observe a dramatically different pattern for acquirers in the right panel of Figure 1. Price effects for commodities and other medical/surgical products are more often negative, particularly for needles, IV administration, and in-vitro diagnostic (IVD) kits, which exhibit negative and significant price effects on the order of 10-15 percent. Second, in stark contrast to the target results, the coefficient estimates for PPIs are often positive, but clustered close to zero. Third, the across-brand results for commodities are larger than the within-brand results, though the differences are not significant within category.

The pooled results are summarized in the right columns of the top panel of Table 2. The commodity coefficients indicate savings of 6.4 percent for acquirers, only 1.4 percentage points of which can be accounted for by renegotiation. There are no significant results for other medical/surgical products, and prices go up slightly (1.1 percent) post-merger for PPIs.

In order to better understand these patterns, we also performed several alternative specifications. First, we estimated the effects of mergers on hospitals' tendency to standardize purchasing within categories, hypothesizing that mergers incentivize systems to consolidate purchasing across vendors in order to achieve better discounts (Noether and May 2017). We estimate a version of specification (1) where the dependent variable is an indicator for whether a hospital had "standardized" purchasing; we categorize a hospital as standardized if it purchased at least 75 percent of units in a product category from a single vendor in

Figure 1: Merger Treatment Effects



Notes: Regression coefficients from specifications (1) and (2), post-merger year $\tau_h + 1$ only. Authors' calculations from PriceGuide data. Bars indicate 95% confidence interval with standard errors clustered at hospital-brand level. Left panel: Targets. Right panel: Acquirers. Circular/blue markers: commodities. Triangles/red markers: other medical/surgical products. Square/green markers: PPIs. Solid markers: specification (1), across-brand price effects. Hollow markers: specification (2), within-brand price effects.

a given year.[12] These results are presented for each product class in the bottom panel of

[12]These regressions are run at the hospital-year level and include u-specific hospital and year fixed effects.

Table 2: Merger Treatment Effects – Pooled

Dependent Variable:	ln(Price)			
Commodities	0.033	0.003	-0.064†	-0.014
	(0.041)	(0.022)	(0.023)	(0.012)
Other Med/Surg	0.002	-0.005	-0.001	-0.004
	(0.008)	(0.005)	(0.004)	(0.003)
PPIs	-0.026†	-0.027†	0.011†	0.006*
	(0.007)	(0.007)	(0.003)	(0.004)
Fixed Effects:	$\theta_{uh} + \theta_{jym}$	$\theta_{uhj} + \theta_{jmy}$	$\theta_{uh} + \theta_{jmy}$	$\theta_{uhj} + \theta_{jmy}$
Treatment:	Targets		Acquirers	

Dependent Variable:	Standardized	
Commodities	0.010	0.019
	(0.062)	(0.031)
Other Med/Surg	-0.030	0.058**
	(0.037)	(0.024)
PPIs	-0.036	0.034
	(0.054)	(0.029)
Fixed Effects:	$\theta_{uh} + \theta_{uy}$	$\theta_{uh} + \theta_{uy}$
Treatment:	Targets	Acquirers

Notes: Authors' calculations from PriceGuide data. * $p < 0.10$, ** $p < 0.05$, † $p < 0.01$. Standard errors clustered at the hospital-brand level in parentheses. Coefficients estimated from pooled specifications (1) and (2). The dependent variable ln(Price) is the logged transaction price measured at the hospital-brand-month-year. The dependent variable in the Standardization regressions is an indicator for whether the hospital bought at least 75% of all units in a product category from a single vendor in a given calendar year. All price specifications include brand-month-year fixed effects. Standardization specification includes hospital and year fixed effects.

Table 2; to fix ideas, the baseline rates of standardization are 70 percent for commodities, 50 percent for other medical/surgical, and 44 percent for PPIs. They are quite noisy – the only marginally significant effect is that acquirers are more likely to standardize other medical/surgical products post merger, and that result is sensitive to measure definition and standard errors.[13]

Second, we examine the concern that merging hospitals exhibit different latent trends in prices: we estimate matched versions of specifications (1) and (2), using a weighted regression after propensity score matching merging hospitals based on beds, Medicare and Medicaid

[13]In Appendix Table A10, we change the standardization threshold from 75 percent to 90 percent; in Appendix Table A8, we estimate standard errors using the wild bootstrap method. Neither alternative specification finds significant standardization effects.

shares of discharges, HMO penetration, teaching and non-profit status, log(admissions), log(technologies), and log(FTEs) (following Dranove and Lindrooth (2003)). The results in Appendix Table A9 are qualitatively and quantitatively consistent with our main results. The main difference is that the matched version finds small, significant within-brand price decreases for other medical/surgical products for both targets and acquirers.

We next examine, as well as possible given the short pre- and post-merger periods available in our data, whether the results above are (1) driven by preexisting differential trends in prices among merging facilities; or (2) biased due to merger effects that develop slowly over time (e.g., due to fixed contracts that take time to renegotiate as in Grennan and Swanson (2018b)). The pooled event study versions of our specifications are shown in Figure 2 below for targets (left panels) and acquirers (right panels), and for commodities (top panels) and PPIs (bottom panels). In each panel, we show one full calendar year pre- and post-merger; the year of merger is highlighted in gray.

While individual relative month point estimates are often noisy, several features stand out. First, there is little evidence of differential pre-trends. Second, there is a clear difference in price levels in the pre- vs. post-merger periods for acquirers' purchase of commodities and targets' purchase of PPIs.[14] Finally, there is no strong evidence that, where merger effects exist, they are continuing to evolve at the end of the time horizon observed.[15] Appendix Figure A2 focuses on several categories with particularly large treatment effects: IV administration kits and needles (for acquirers) and resynchronization defibrillators and pacemakers (for targets); the general patterns documented here are similar within individual case studies. These results are also robust to longer pre- and post-merger periods: Appendix Figure A1 demonstrates that our short pre-/post-merger window does not miss delayed realizations of price effects, nor does it miss a substantial pre-trend.

Given the relatively high spend on PPIs vs. commodities and other medical/surgical products, these results indicate that targets achieve higher savings post-merger than acquirers. Across our 47 product categories, targets save an estimated \$14,669 per month on average, whereas acquirers experience an average net increase in spending of \$27 (calculation details in Appendix D).

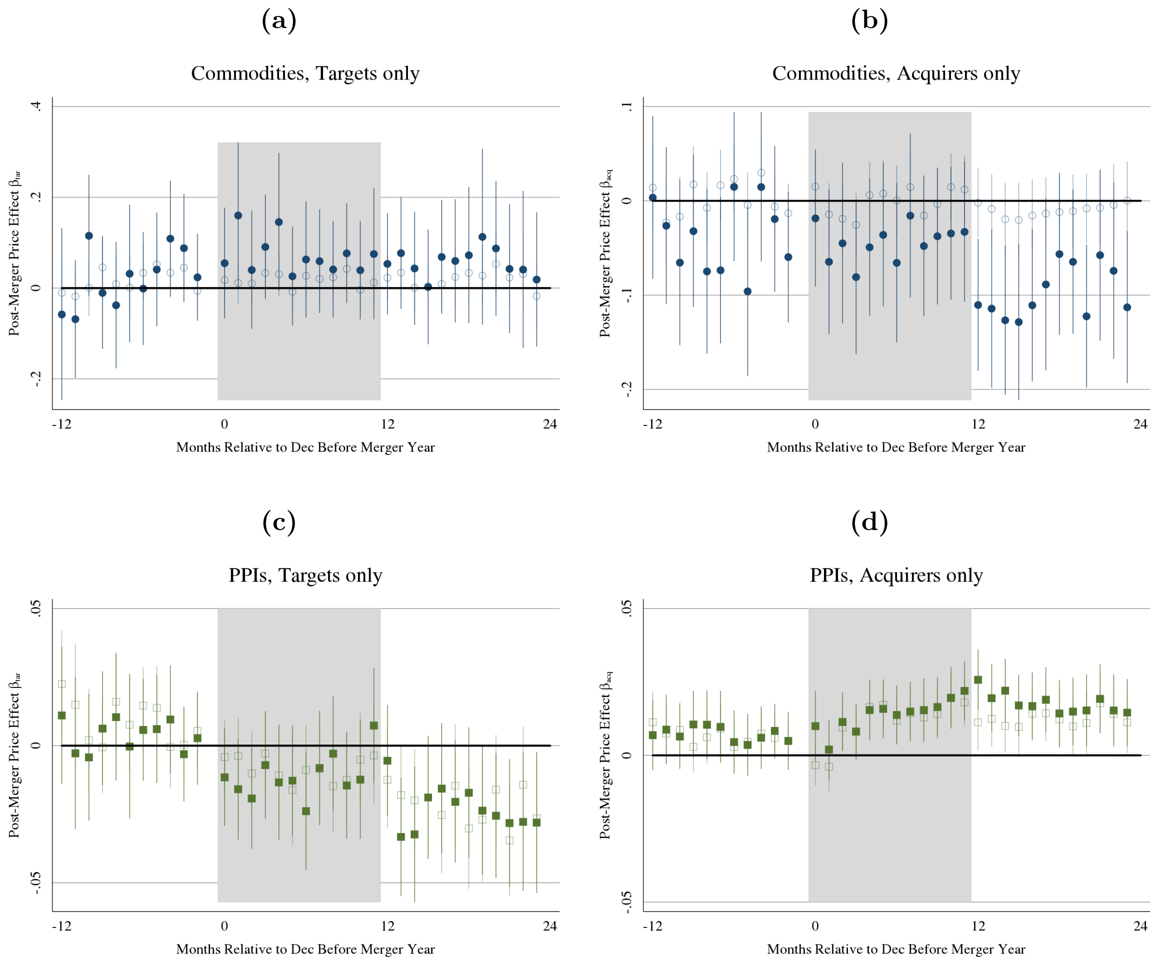
3.2.1 Exploring mechanisms using treatment effect heterogeneity

As noted above, much of the literature regarding mergers and cost efficiencies focuses on advantages associated with firm size, perhaps interacted with greater channeling ability.

[14] Interestingly, savings to acquirers on commodities are achieved only in the calendar year after the merger year, whereas savings to targets on PPIs begin to manifest within the merger year.

[15] Table A11 shows the estimates if we include τ_h as a post-merger year. The results are smaller and more precise, as expected.

Figure 2: Merger Treatment Effects – Event Studies



Notes: Authors' calculations from PriceGuide data. Regression coefficients from pooled event study version of specifications (1) and (2), each month within one year of merger year τ_h. Hold-out date is December of last pre-merger year. Bars indicate the 95% confidence interval with standard errors clustered by hospital-brand. Solid markers denote estimates from specification (1), which represent across-brand price effects. Hollow markers denote estimates from specification (2), represending within-brand price effects.

Within our sample, we observe variation in both pre-merger size and the firm size change induced by the merger. Though almost all of our transactions involve 1-2 target hospitals, our acquirer systems range from very small (1 or 2 hospitals) to large (over 70 hospitals). The effect of target and acquirer size on purchasing is ex ante ambiguous. The "concavity" theory of Chipty and Snyder (1999) and others predicts largest effects for small targets joining large systems, with small or zero effects for large acquirers. On the other hand, efficiencies may be due to improved management practices, and there may be economies or diseconomies of scale in sharing good management between merging hospitals.

The top two rows in Table 3 show separate results for mergers involving small (1-3 hospitals) vs. large (4+ hospitals) acquirers. For the sake of brevity, we focus on PPI prices for targets, and commodity prices for acquirers (full results available in Table A12). Within targets, savings on PPIs are much larger among targets acquired by independent hospitals or small systems (5.2 percent) than among targets acquired by large systems (0.9 percent). In contrast, within acquirer hospitals, savings are larger among acquirers that are in large systems *prior to the merger* (6.7 percent) than among small acquirers (an insignificant 3.7 percent).

Table 3: Merger Treatment Effects – Heterogeneity

	Targets/PPIs					Acquirers/Commodities				
		$\theta_{uh}+\theta_{jmy}$		$\theta_{uhj}+\theta_{jmy}$			$\theta_{uh}+\theta_{jmy}$		$\theta_{uhj}+\theta_{jmy}$	
	N_{tar}	β	SE	β	SE	N_{acq}	β	SE	β	SE
Acquirer Size										
Small	12	-0.052†	(0.012)	-0.035†	(0.011)	26	-0.037	(0.033)	-0.045**	(0.018)
Large	17	-0.009	(0.008)	-0.041†	(0.013)	58	-0.067**	(0.030)	-0.001	(0.019)
Market Exposure										
In HRR	12	-0.059†	(0.011)	-0.062†	(0.013)	37	-0.017	(0.028)	-0.030*	(0.017)
Out of HRR	17	0.004	(0.008)	-0.012	(0.009)	47	-0.097†	(0.034)	-0.021	(0.021)
Vendor Market Structure										
High	29	-0.027**	(0.012)	-0.042†	(0.011)	84	-0.045	(0.033)	-0.025	(0.017)
Low	29	-0.028†	(0.009)	-0.036†	(0.010)	84	-0.063†	(0.020)	-0.035†	(0.008)
Controlling for Output Price										
Post-Merger	29	-0.026†	(0.007)	-0.036†	(0.008)	84	-0.046**	(0.023)	-0.028**	(0.014)
ln(Output Price)		-0.003	(0.009)	0.023†	(0.008)		-0.021	(0.025)	-0.016	(0.013)
Standardization Interaction										
Post-Merger	29	-0.029†	(0.009)	-0.036†	(0.010)	80	-0.019	(0.032)	-0.048†	(0.017)
Standardized		-0.007	(0.005)	0.004	(0.005)		-0.018	(0.021)	-0.005	(0.010)
Post X Std.		-0.004	(0.011)	-0.015	(0.011)		-0.050	(0.039)	0.044**	(0.022)

Notes: Authors' calculations from PriceGuide data. * $p < 0.10$, ** $p < 0.05$, † $p < 0.01$. Standard errors clustered at the hospital-brand level in parentheses. Coefficients estimated from pooled specifications (1) and (2). The dependent variable is the logged transaction price measured at the hospital-brand-month-year. Small acquirers are hospital systems consisting of 1-3 hospitals pre-merger, and large acquirers are hospital systems with more than 3 hospitals. A target is categorized as "In HRR" if there is at least one hospital in the acquiring system in the same HRR, and vice versa. Product categories are classified as "High" concentration if its vendor HHI is above the median within its product class. ln(Output Price) is estimated using the HCRIS as in Dafny et al. (2017). Standardization is an indicator for whether the hospital purchased at least 75% of all units in a product category from a single vendor in a given calendar year.

In making sense of these results, it is important to note that relative size of acquirers and targets is closely related to whether the merger involves market overlap. As noted in Schmitt (2017), many of the mergers in the recent "great reconsolidation" involve large hospital systems acquiring hospitals in distant geographic markets. We next split the treatment effects according to whether any of the merging hospitals share a hospital referral region (HRR). Heterogeneity in merger effects by market overlap may be due to local economies of scale in management/distribution of inputs, to local diffusion of management practices, or to the relative roles of bargaining power vs. bargaining position in mediating merger efficiencies.

We compare treatment effects for in- vs. out-of-market mergers in the second pair of rows in Table 3. The merger effects previously documented for targets' purchase of PPIs are concentrated in in-market mergers. In contrast, for acquirers the large savings on commodities are concentrated in out-of-market mergers. These results go hand-in-hand with the size results above, as out-of-market mergers within our sample typically involve large acquirers and in-market mergers typically involve small acquirers. Our results regarding target hospitals and PPIs echo Dranove and Lindrooth (2003), in which cost savings are greatest when previously independent hospitals integrate under a single license and consolidate facilities. Our results regarding acquirer hospitals and commodities are more consistent with the large out-of-market merger effects documented in Schmitt (2017), though those effects were strongest for the *targets* in out-of-market acquisitions.

Finally, we examine whether merger effects are mediated by supply-side market structure. To this end, we separate UMDNS codes within each product class into those above or below the median HHI for the class. As noted in Table 1, the product categories analyzed in this paper are almost all moderate-high concentration according to typical FTC and DOJ standards. That said, the mean "High HHI" commodity has an HHI of 0.478, vs. 0.236 among the "Low HHI" commodities; the same measures among PPIs are 0.497 and 0.227, respectively. The third pair of rows in Table 3 show that there is no meaningful or statistically significant difference in price effects as a function of supplier competition.

3.2.2 Supply-side and demand-side market power

The fourth pair of rows in Table 3 examine whether the cost effects documented above are muted due to mergers causing hospitals' supply side and demand side market power to increase concurrently. For example, if merger-enabled supply side market power allowed hospitals to increase procedure prices, some of that pie could be shared with suppliers and mitigate cost decreases due to increased demand side market power. To that end, we estimate our same input price regression specifications, *controlling for* output prices. We employ the method described in Dafny et al. (2017) to infer hospital prices from HCRIS reports.

For targets and PPIs, controlling for hospitals' downstream prices does not change the estimated merger treatment effect – merger effects on targets' PPI prices are not understated due to price increases. If anything, adding this simple control *reduces* the estimated effect of merging on acquirers' commodity prices; this may be driven in part by some contemporaneous effect among the large, expanding hospital systems.

3.2.3 Standardization and renegotiation

The final set of rows in Table 3 examines the interaction between merger effects and standardization. We estimate a simple modification of the above specifications, in which the year-of and post-merger dummies are interacted with a dummy for hospital-category-year-level standardization.

The results confirm that targets receive savings on PPIs from merging, but the merger price effect is not significantly amplified for hospital-categories that standardize. In contrast, the results are very noisy for acquirers' commodity costs: we estimate a large negative coefficient on the post-merger dummy interacted with standardization in the across-brand specification; this interaction is (marginally) significantly positive in the within-brand specification. In sum, we find no consistent evidence that post-merger standardization is a substantial source of savings for any merging party.

4 Discussion

The US hospital industry has experienced a large amount of contentious consolidation via mergers over the last several decades. Marginal cost efficiencies have been perhaps the most common justification offered for these mergers, often appealing to notions that "buyer power" is increasing in hospital system size. Prior research examining aggregated accounting measures of hospital costs that have been available previously has found mixed results.

In this study, we use data on all purchase orders issued by a large set of US hospitals 2009-15 in order to conduct a detailed examination of the effects of mergers on the prices paid for medical/surgical supplies, an important component of hospital marginal costs. The most robust finding of efficiencies is target savings of 2.6 percent on targets' purchase of physician preference items.

The variety of product categories in the data allows us to examine mechanisms underlying "buyer power" (which has previously been studied in theory and in case studies of specific product markets). We examine heterogeneity in merger treatment effects across different product categories, and by acquirer size, local vs. out-of-market, and vendor market concentration. We find that the observed savings on PPIs is driven by small, local mergers. To the extent that such results are driven by concavity in the surplus function as in Chipty and Snyder (1999), such efficiencies must only apply locally. Alternatively, these savings may be consistent with integration and transfer of managerial practices. For less-expensive commodity products, savings are strongest for large acquirers, suggesting limited focus on or success in managing commodity costs among smaller systems.

The largest estimated savings, by targets on PPIs, can entirely be attributed to renegotiation, rather than brand switching. This transfer of surplus from device manufacturers to hospitals is suggestive of increased monopsony power and may not increase efficiency; e.g., they may negatively impact dynamic incentives of suppliers to innovate or maintain product quality or manufacturing reliability (see discussion in Hemphill and Rose (2018)).

We offer these and all results with the caveat that our sample size of mergers is smaller than we would like due to the relative newness of purchasing order data availability. However, we believe the detail and breadth of the purchasing data brings new light to the study of hospitals broadly, and mergers specifically.

For hospital mergers in particular, another important phenomenon to consider is the simultaneity of input market negotiation and output market negotiation. We control for this using a proxy for hospital output prices, and it does not have a material effect on estimates. However, a more detailed study would require matching hospital purchasing data with private insurer claims, and modeling demand and negotiated prices explicitly in both upstream and downstream markets. We see this as an important area for future research.

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ELECTRONIC APPENDICES – NOT FOR PRINT PUBLICATION

A Merger Literature

As noted in Section 1, hospitals have consolidated substantially through horizontal mergers. Much of this consolidation took place during the merger wave of the 1990s; more recently, the Affordable Care Act (ACA) spurred another merger wave, with 105 deals reported in 2012 alone, up from 50 to 60 annually in the pre-recession years of 2005-2007 (Dafny 2014). The purported reasons for this consolidation and "great reconsolidation" are varied. The merger wave of the 1990s was coincident with the rise of managed care and it became conventional wisdom that this relationship was causal – Town et al. (2007) dispute this, noting that panel data analyses do not suggest that managed care penetration is significantly related to hospital consolidation. The merger wave during the ACA years has been associated with hospitals anticipating the need for large, coordinated organizations to manage population health under payment reforms such as bundled payment and Accountable Care Organizations (Dafny 2014).

Efficiencies represent a key justification used by hospitals in defending their ability to merge, as they present opportunities to lower price and improve quality. In survey data, hospital executives commonly cite the following reasons for merging: 1) strengthening their financial position, 2) achieving operating efficiencies, and 3) consolidating services (Vogt and Town 2006). The general literature to date on the effects of hospital concentration has not suggested that consolidation improves efficiency. The research on the quality, price, and cost effects of mergers is summarized in Appendix Table A1. While an exhaustive review of the evidence is outside the scope of this paper, the dominant narrative appears to be one of mergers decreasing quality, increasing price, and having a mixed effect on costs.

Table A1: Summary of Mergers Literature

Outcome	Efficiency Gains	Null Effects or Efficiency Losses
Quality	Romano and Balan (2011): some quality indicators, Evanston/Highland Park merger, 1998-03	Beckert et al. (2012): reduced responsiveness of demand to mortality, UK, 2000s; Capps (2005): mortality for AMI, heart failure, NY, 1995-2000; Ho and Hamilton (2000): AMI, stroke, early discharge of newborns, 1992-1995; Romano and Balan (2011): some quality indicators, Evanston/Highland Park merger, 1998-03; Town et al. (2006): increased uninsurance, 1991-2003
Price	Spang et al. (2001): 5% effects, 1989-1997; Thompson (2011): 1/4 insurers, New Hanover/Cape Fear merger, 1998	Capps and Dranove (2004): 9/12 mergers, 1997-2001; Dafny (2009): 40% effects, 1989-1996; Dafny et al. (2017): cross-market mergers involving adjacent markets; Haas-Wilson and Garmon (2011): 20% effects for Evanston/Highland Park merger, negligible effects for St. Therese/Victory merger; Krishnan (2001): 16.5% increases in OH, 11.8% increases in CA, 1994-1995; Sacher and Vita (2001): 22% effects, Dominican/Watsonville merger, 1986-1996; Tenn (2011): 28.4-44.2% effects, Sutter/Summit merger, 1997-2002; Thompson (2011): 3/4 insurers, New Hanover/Cape Fear merger, 1998
Cost	Dranove and Lindrooth (2003): single license post-acquisition; Harrison (2010): short-run costs; Schmitt (2017): targets in out-of-market acquisitions, large multi-hospital group acquisitions	Dranove and Lindrooth (2003): separate licenses post-acquisition; Harrison (2010): long-run costs; Schmitt (2017): acquirers, in-market acquisitions, small-group/independent hospital acquisitions

Note: For the sake of brevity, we use "Efficiency Gains" to refer to documented increases in quality, decreases in price, or decreases in costs. We use "Null Effects or Efficiency Losses" to refer to the documented lack of "Efficiency Gains" or to decreases in quality, increases in price, or increases in costs.

B Data Appendix

The primary data used in this study come from a unique database of all supply purchases made by over 1,200 US hospitals during the period 2009-2015. The data are from the PriceGuide™ benchmarking service (hereafter, "PriceGuide data") offered by the ECRI Institute, a non-profit health care research organization. For each transaction, we observe price, quantity, transaction month, and supplier for a wide range of product categories.

The reported data are of high quality because they are typically transmitted as a direct extract from a hospital's materials management database. Hospitals have strong incentives to report accurately because the analytics the benchmarking service's web portal provides are based on comparing the hospital's submitted data to that of others in the database.[16]

The raw transactions data contain 116 million observations for 2,876 members across 3,394 product categories and 2.7 million SKUs. Our analyses include 47 important product categories, defined by their UMDNS codes. We restricted to the top 50 categories by spending or number of transactions, yielding 71 categories total. From these, we excluded categories that were too broad (e.g., "food item") or where data quality seemed to be an issue.[17] Next, creating the final analysis file required two key steps for each product category: (1) rationalizing the multiple units of measure in which different transactions' quantities were reported, in order to analyze price for a common quantity across transactions;[18] and (2) generating brand IDs, in order to appropriately control for brand-specific price trends.

Regarding the first step, although many medical and surgical product categories are sold by the unit (a single coronary stent, e.g.), others are sold in pairs, boxes, cases, etc. The transactions data indicates this distinction in the "unit of measure" field, and further notes how many subunits are in each unit of measure using a "conversion factor" field. In order to perform our analyses on the cleanest and most internally-consistent transactions data possible, we transformed all transactions into price per single unit and quantity of single units purchased. We also excluded UMDNS codes with inconsistent or missing quantity data.[19] The next Section details the second step, in which we categorize SKUs into brand

[16]Nonetheless, there is some evidence that the data are incomplete. For example, we find it unrealistic that some broadly used categories (e.g. examination gloves) do not include data from all hospitals.

[17]We did this based on "reasonableness" of the observed price variation – categories for which the coefficient of variation in price exceeded 10 were excluded – and selected categories by hand that seemed excessively broad based on their UMDNS names (e.g., "office supplies"). The list of product categories excluded by hand is 88889, 99936, 88885, 88884, 88883, 88695, 88539, 88311, 88073, and 16101.

[18]We also excluded product categories where the modal unit of measure accounted for less than one-half of the data or where the quantity conversion factor was missing for at least one-third of the data.

[19]Specifically, we excluded UMDNS codes for which the conversion factor (e.g., ten units per box) was missing more than 1/3 of the time, or for which the modal unit of measure (e.g., "box" vs. "case") accounted for less than 50 percent of the data.

categories.

B.1 Identifying Brands in the Transaction Data

The absence of a brand identifier in the database creates a problem of sparsity, in which many SKUs are purchased by only a small number of hospitals, or in only a small number of months. The most thorough method we employed to identify brands, for a subset of products, involved examining manufacturer catalogs, finding likely brand names, searching for similar strings within the item description field, and validating SKUs for those brands against the catalog numbers. This was infeasible for all product categories due to the large number of manufacturers and SKUs. Additionally, many manufacturers' websites were found to be difficult to navigate, particularly once we extended the analysis beyond high-dollar physician preference items. Finally, the item description field was often uninformative as to brand. Hence, we used an algorithmic approach to assign brand identifiers for the other product categories.

Our preferred algorithm implements the Random Effect Expectation-Maximization (RE-EM) estimation method from Sela and Simonoff (2011), which is an adaptation of a recursive partitioning tree algorithm to allow for group effects. With no particular assumption made about the significance of each letter within a SKU, recursive partitioning tree allows us to obtain overfitting-proof groupings that minimizes the 10-fold cross validation error. Furthermore, the group effects in the RE-EM estimation method allow us to control for systematic heterogeneity in price across hospital-time.

Given a transaction $i = 1, \ldots, N$ where N is the size of the dataset within a UMDNS code, price p_i of the transaction, dummy matrix Z_i indicating each transaction's hospital-time group, group effect b_i, and attribute vector $D_i = \{d_{i1}, \ldots, d_{iL}\}$ where d_{il} is the lth digit of the SKU associated with transaction i, the RE-EM proceeds as follows:

1. Initialize estimated group effect $\hat{b_i}$ to zero.

2. Iterate through the following steps until the estimated hospital-time effect $\hat{b_i}$ converges.

    (a) Estimate a regression tree with recursive partitioning on price adjusted by hospital-time group effect, $p_i - Z_i\hat{b_i}$ with attributes D_i. Take the terminal nodes, $j \in J$, of the tree and create an indicator variable, $I(D_i \in j)$.

    (b) Fit a linear model, $p_i = Z_i b_i + I(D_i \in j)\mu_p + \epsilon_i$ and extract $\hat{b_i}$ from the model.

3. Once $\hat{b_i}$ converges, take the final grouping $j \in J$ and use it as the new product identifier for each i.

At each iteration of step (2a), the tree is pruned using 10-fold cross validation at each split; the model retains the simplest tree with cross validation error no more than one standard error away from the tree with the minimum cross validation error.

With this method, we categorized 149,543 SKUs across 47 UMDNS codes into 6,881 RE-EM brands. For surgical staplers and drug-eluting coronary stents, which we validated by hand, we identified 3.8 RE-EM brands per "true" stapler brand, 0.8 RE-EM brands per "true" drug-eluting stent brand.

B.2 Identifying Mergers

We combine our detailed transaction data with data from our M&A roster, which we obtained from Cooper et al. (2015). These data represent a detailed roster of hospital mergers from 2000-2014. Further information on this data can be found in the Online Appendix to Cooper et al. (2015). The first column of Table A2 displays the characteristics of hospitals involved in M&A transactions in the full sample of AHA data from 2000-2014. The second column focuses on transactions in the period for which we have hospital cost data: 2009-2014. In our main analysis, we limit to mergers for hospitals we were able to link to the PriceGuide database; the third column describes these transactions and hospitals. Finally, the fourth column limits the sample to the *first* transactions observed for each target or acquirer in the PriceGuide data, focusing on those transactions for which we observe at least one year of pre- and post-merger data.[20]

Focusing on the first panel, the Table shows that about half of the mergers in 2000-2015 took place in 2009-2015, so this time period is highly relevant for the current analysis. The third column illustrates that the PriceGuide database covers approximately 28 percent of the hospitals involved in M&A transactions in 2009-2015. The most severe limitation is in the fourth column – because the PriceGuide members join the database over time, we only have both pre- and post-merger data for about 18 percent of the PriceGuide merger data. This is a substantial limitation, as these are the transactions and hospitals that will identify our differences-in-differences estimates. However, we still have 81 case studies—covering 33 target hospitals and 98 acquirers—for carefully examining the effects of mergers for a variety of product categories and consider this a meaningful sample on that basis.

The facilities in the purchase order data voluntarily joined a subscription service that allows them to benchmark their own prices and quantities to those of other members in the database and thus may not be a random sample of US hospitals. In particular, subscription is costly, so we expect hospitals with greater concerns about supply costs to be overrep-

[20] Post-merger here refers to years following the year of the merger (i.e. $y > \tau_h$).

Table A2: Merger Sample Restrictions

	(1)	(2)	(3)	(4)
	Full Sample, 2001-2014	Full Sample, 2009-2014	ECRI Hospitals, 2009-2014	ECRI Hospitals, Full Support, 2009-2014
Transaction Characteristics				
Number of Transactions	828	445	256	81
Number of Targets	1,092	661	183	33
Number of Acquirers	2,199	1,753	390	98
Median Target Size	1	1	1	2
Median Acquirer Size	45	31	10	13
Hospital Characteristics				
Beds	168.6	166.6	270.8	280.3
FTEs	914.1	960.3	1,773.6	1,843.9
Technologies	40.6	45.2	62.5	64.0
Admissions	7,419.8	7,367.1	13,188.5	13,662.0
Teaching	0.231	0.245	0.401	0.412
Non-Profit	0.611	0.610	0.783	0.741
CMI	1.428	1.428	1.534	1.541
Percent Medicaid	0.165	0.172	0.191	0.197
Percent Medicare	0.495	0.505	0.463	0.457
Output Price	9,256	9,256	10,561	10,726
Metro	0.475	0.617	0.699	0.732
Region				
East North Central	0.156	0.157	0.163	0.174
East South Central	0.089	0.088	0.037	0.036
Middle Atlantic	0.093	0.089	0.156	0.133
Mountain	0.075	0.078	0.097	0.129
New Endland	0.040	0.040	0.087	0.090
Pacific	0.106	0.105	0.147	0.127
South Atlantic	0.151	0.151	0.156	0.192
West North Central	0.145	0.145	0.063	0.047
West South Central	0.145	0.147	0.093	0.071

Notes: Each column reports the counts and characteristics of merging hospitals in the data at varying levels of sample restrictions. Column (1) reports counts and characteristics of all mergers in our combined merger roster from 2001-2014. Column (2) reports data on mergers that overlap with the timing of the ECRI data. Column (3) presents the mergers for which there exists any data in the ECRI database. And, Column (4) presents mergers in the ECRI data for which we have adequate pre and post data to perform our difference-in-difference estimation. In Columns (3) and (4), the median target size is calculated over the targets which exist in the ECRI data; median acquirer size is calculated over all merging hospitals (targets and acquirers) in the data. Data on metropolitican area status and case-mix index (CMI) come from CMS Medicare Impact Files. Data on census division, beds, FTEs, technologies, admissions, teaching status, non-profit status, Medicare and Medicaid share come from the AHA Annual Survey. Output price is calculated using data from the CMS HCRIS and Medicare Impact Files as in Dafny et al. (2017).

resented in the database – for example, in a survey of database members, "cost reduction on PPIs" and "cost reduction on commodities" were the first and second (and nearly tied) most commonly cited reasons for joining. This is in accord with our own conversations with purchasing managers who cite a broad array of reasons and product areas as motivations for benchmarking. Table A2 shows that, on balance, our sample of mergers covers relatively larger hospitals, treating sicker patients, and more often in urban areas.

C Medical Supply Usage and Purchasing

For physician preference technologies, usage is driven by physicians choosing which brand to use to treat a given patient, while prices are determined in negotiation between a hospital administrator and a representative of the brand's manufacturer. Hospitals typically rely on the services of group purchasing organizations (GPOs) to negotiate contracts for many product categories, but GPO prices are used as a starting point for direct hospital-manufacturer negotiations for physician preference items and capital equipment (Schneller 2009). For PPIs, there is no "search" in the conventional sense, as a given brand can only be purchased directly from its manufacturer. For commodities, a given brand may be sold by multiple vendors.

Contracts typically specify a price for the contract duration, often a year. In the short run, hospitals are reimbursed a fixed amount by private or public insurers based on the services they provide, and so supply prices come directly from the hospital's bottom line. In our conversations with industry participants, the purchasing practices via which these contracts are negotiated vary widely across organizations. Some hospitals have large materials management or purchasing departments with agents who specialize in negotiations. Sometimes a large business unit, such as a catheter lab in the case of stents, will coordinate its own purchasing separately from the rest of the hospital. Finally, hospitals vary in access to information on the prices other hospitals pay via GPOs, hospital system membership, or informal networks of peers.

C.1 GPOs and merger effects

Given the impact that GPOs may have on purchasing, it is natural to wonder how this is borne out in the data. For example, if merging hospitals switch GPOs, then one might worry about the extent to which we actually observe prices for these hospitals post-merger. We address this concern by estimating the responses of quantities in a specification similar to our standardization model. Here, the dependent variables are an indicator for whether the hospital purchased any of a given product category in a year and log(quantity) for years in which any quantity was observed. Appendix Table A3 reports the results of this exercise. In general, we find no evidence that quantity declines post-merger in any substantial way.[21]

[21]The exception to this is that we observe a negative 4.8 percent in the probability that we observe acquirers purchasing any products from a given PPI category. This estimate is driven largely by Drug Eluting Stents, for which we observe a 17.5 percent decline in purchase probability. While this result is large, the fact that it is isolated to one product category helps alleviate concerns that hospitals systematically exit the data post-merger.

Table A3: Merger Treatment Effects – Pooled, Quantity

	Targets		Acquirers	
	$Q > 0$	$ln(Q)$	$Q > 0$	$ln(Q)$
Commodities				
Post-Merger	0.052	0.209	-0.020	0.006
	(0.038)	(0.192)	(0.026)	(0.088)
Other Med/Surg				
Post-Merger	0.037*	0.003	0.008	0.092**
	(0.023)	(0.055)	(0.017)	(0.038)
PPIs				
Post-Merger	-0.014	-0.015	-0.048†	0.041
	(0.026)	(0.059)	(0.017)	(0.032)

Notes: Authors' calculations from PriceGuide data. * $p < 0.10$, ** $p < 0.05$, † $p < 0.01$. Standard errors clustered at the hospital level in parentheses. Coefficients estimated from pooled specifications (1) with hospital and year fixed-effects. The dependent variable $Q > 0$ is an indicator for whether a hospital purchased any items in a given product category. The dependent variable $ln(Q)$ denotes the log quantity purchased in a given product category-year, conditional on any purchase.

D Deriving Estimated Savings from Treatment Effects

A main object of interest for this study is the estimated yearly savings a hospital might experience given the treatment effects we observe. In order to generate these numbers, we calculate average yearly savings for class $\mathcal{C}$ as:

$$\widehat{save}_{\mathcal{C}} = \sum_{u \in \mathcal{C}} \hat{\beta}_u * (\overline{spend}_{uhy|y<\tau_h}),$$

where β_u represents the target- or acquirer-specific treatment effect for UMDNS code u and $(\overline{spend}_{uhy|y<\tau_h})$ is the target- or acquirer-specific pre-merger average yearly spending per hospital. We aggregate these across categories within product class $\mathcal{C}$ to obtain estimates of average yearly savings for target and acquirer hospitals. Table A4 shows the details for these estimates. We find that target hospitals save \$198,375 on PPIs, but pay more for other medical surgical items (\$8,241) and commodities (\$14,113), for a net savings of \$176,022 post-merger. We find that acquirers save \$65,241 on commodities and \$14,610 on other medical/surgical items. However, this is entirely offset by increased spending on PPIs of \$80,172, for a net loss of \$320 per year on average.

Alternatively, we could calculate estimated savings by broad product class using total average spending across UMDNS codes and the pooled estimates from our stacked regressions presented in Table 2. Table A6 shows the details for these estimates. Here, we find that targets save \$165,056 and acquirers lose \$19,735 per year on average.

To clarify the source of the difference between the two approaches, note that Table 2 presents the treatment effect estimates from our stacked regressions, where β is estimated by pooling all UMDNS codes in a given class and weighting observations by average annual spending on each category.[22] The covariance between spending and β_u across product categories generates the differences between our two methods of calculating total implied savings.

[22]Results are similar if we instead simply average the category-specific coefficients in Table A4, weighting each coefficient by average annual spending.

Table A4: Estimated Savings Using Across-Brand Merger Effects

	$Gini_{uh\|jmy}$	Targets $\overline{spend}_u$	β_u	SE_u	$\widehat{save}_u$	Acquirers $\overline{spend}$	β_u	SE_u	$\widehat{save}_u$
Tags/Labels	0.11	7,477	0.088	0.158	-659	9,288	-0.073	0.098	675
Surgical Drapes	0.08	34,507	-0.061	0.067	2,116	31,987	-0.031	0.042	980
Needles	0.13	44,893	-0.046	0.075	2,071	51,321	-0.095	0.055	4,875
Dressings	0.09	43,018	-0.015	0.039	626	75,580	-0.001	0.020	73
Drill Bits	0.08	65,296	-0.005	0.016	349	81,434	-0.026	0.009	2,138
IV Administration Kits	0.14	89,469	-0.163	0.082	14,610	106,063	-0.158	0.072	16,759
Batteries	0.08	19,195	0.047	0.088	-910	34,734	0.007	0.057	-231
IVD Kits	0.12	338,805	0.095	0.076	-32,316	422,612	-0.095	0.042	39,972
Commodities Total		642,660			-14,113	813,019			65,241
Sutures Nylon Monofilament	0.06	8,999	0.078	0.026	-705	15,549	-0.019	0.014	299
Bone Wires	0.13	21,459	-0.053	0.046	1,145	18,124	-0.052	0.041	946
Angiography Catheters	0.10	42,591	0.007	0.032	-290	25,231	-0.050	0.033	1,269
Tracheal Tubes	0.15	26,843	0.046	0.081	-1,236	39,192	-0.037	0.032	1,441
Sutures	0.10	32,211	0.044	0.045	-1,424	29,982	0.022	0.030	-669
Polypropylene Sutures	0.07	35,403	-0.040	0.058	1,407	49,679	0.001	0.023	-34
Trocars	0.09	72,804	0.080	0.044	-5,816	80,086	-0.013	0.039	1,024
Suture Anchors	0.07	62,562	0.035	0.032	-2,193	98,318	0.005	0.011	-455
GI Staples	0.18	58,283	-0.081	0.141	4,736	183,210	-0.081	0.065	14,880
Electrosurgical Forceps	0.12	100,609	0.017	0.072	-1,746	155,306	-0.002	0.032	379
Polymeric Mesh	0.06	89,673	-0.019	0.027	1,730	148,059	0.020	0.016	-2,907
Bone Nails	0.07	149,845	-0.043	0.025	6,466	132,104	0.013	0.017	-1,678
Trauma Bone Plates	0.05	135,915	-0.029	0.011	3,916	133,282	-0.012	0.007	1,587
Surgical Staplers	0.08	161,796	0.017	0.028	-2,777	163,854	0.008	0.016	-1,317
Bone Implant Putty	0.05	207,381	0.010	0.024	-2,047	152,812	0.012	0.011	-1,848
Spinal Bone Plates	0.08	184,493	0.091	0.036	-16,784	153,061	-0.012	0.019	1,849
Guiding Catheters	0.09	201,432	0.024	0.030	-4,787	186,996	-0.010	0.016	1,777
Guide Wires	0.09	225,899	0.002	0.018	-420	247,702	0.012	0.009	-2,919
Trauma Bone Screws	0.08	174,039	-0.006	0.013	1,089	231,470	-0.010	0.006	2,323
Bone Grafts	0.04	275,187	-0.112	0.070	30,721	352,701	-0.009	0.007	3,243
Ablation/Mapping Catheters	0.07	491,229	0.001	0.018	-313	398,176	-0.054	0.011	21,412
Aortic Stents	0.03	370,289	-0.002	0.032	706	429,992	0.017	0.029	-7,410
Spinal Bone Screws	0.10	783,374	0.025	0.020	-19,617	716,334	0.026	0.014	-18,579
Other Med/Surg Total		3,912,317			-8,241	4,141,220			14,610
Intraocular Lenses	0.05	85,130	0.019	0.016	-1,654	112,267	-0.008	0.007	922
Spinal Rod Implants	0.09	84,839	0.035	0.036	-2,994	78,096	0.011	0.025	-889
Allografts	0.05	121,461	0.038	0.043	-4,659	170,192	0.020	0.024	-3,392
Embolization Coil	0.04	126,795	0.096	0.059	-12,156	190,202	0.027	0.018	-5,130
Mammary Prosth.	0.04	198,467	-0.041	0.019	8,090	266,688	-0.003	0.008	918
Acetabular Hip Prosth.	0.12	212,804	-0.031	0.035	6,650	191,340	0.029	0.026	-5,518
Spinal Stimulators	0.05	514,980	0.014	0.022	-6,959	379,773	0.019	0.015	-7,403
Tibial Knee Prosth.	0.08	416,882	-0.042	0.027	17,681	305,852	-0.011	0.016	3,365
Femoral Hip Prosth.	0.10	472,522	-0.094	0.024	44,208	351,485	0.009	0.016	-3,258
Pacemakers	0.07	549,356	-0.094	0.021	51,567	481,747	0.012	0.008	-5,918
Cardiac Valve Prosth.	0.07	419,883	0.001	0.015	-530	440,065	0.013	0.009	-5,778
Femoral Knee Prosth.	0.07	542,193	-0.059	0.022	31,813	415,035	-0.002	0.011	831
Spinal Spacers	0.06	596,326	0.110	0.026	-65,657	543,893	0.026	0.013	-14,371
Cardioverter Defib.	0.05	816,792	-0.064	0.028	51,934	720,423	0.021	0.011	-14,996
Resynchronization Defib.	0.05	852,969	-0.092	0.038	78,425	719,977	0.015	0.012	-10,960
Drug Eluting Stents	0.04	1,436,850	-0.002	0.010	2,614	1,140,904	0.008	0.006	-8,593
PPIs Total		7,448,249			198,375	6,507,939			-80,172
Grand Total		12,003,226			176,022	11,462,178			-320

Notes: Authors' calculations from PriceGuide data. Estimated savings numbers calculating by totaling expected savings across product categories as described in Appendix D. $Gini_{uh|jmy}$ presents Gini coefficient for the product category u, for prices calculated across hospitals within product-month and averaged across product-months. $\overline{spend}_u$ presents the average pre-merger spending for target and acquirer hospitals. β_u presents the merger treatment effect as estimated from equation (1) and SE presents the corresponding standard error, clustered at the hospital-brand level. $\widehat{save}_u$ denotes the estimated savings per hospital year based on β_u and the pre-merger spending levels.

Table A5: Estimated Savings Using Within-Brand Merger Effects

		Targets				Acquirers			
	$Gini_{uh\|jmy}$	$\overline{spend}_u$	β_u	SE_u	$\widehat{save}_u$	$\overline{spend}_u$	β_u	SE_u	$\widehat{save}_u$
Tags/Labels	0.11	7,477	0.136	0.090	-1,017	9,288	-0.066	0.065	613
Surgical Drapes	0.08	34,507	-0.011	0.032	365	31,987	0.016	0.021	-498
Needles	0.13	44,893	0.006	0.051	-263	51,321	-0.032	0.035	1,647
Dressings	0.09	43,018	-0.023	0.022	989	75,580	-0.010	0.015	724
Drill Bits	0.08	65,296	-0.019	0.011	1,234	81,434	-0.029	0.007	2,338
IV Administration Kits	0.14	89,469	0.006	0.054	-521	106,063	-0.204	0.057	21,683
Batteries	0.08	19,195	0.032	0.030	-619	34,734	0.020	0.028	-682
IVD Kits	0.12	338,805	0.005	0.027	-1,621	422,612	-0.009	0.015	3,880
Commodities Total		642,660			-1,452	813,019			29,705
Sutures Nylon Monofilament	0.06	8,999	0.047	0.017	-424	15,549	-0.010	0.015	156
Bone Wires	0.13	21,459	-0.017	0.029	360	18,124	-0.077	0.034	1,403
Angiography Catheters	0.10	42,591	-0.008	0.028	356	25,231	-0.035	0.027	891
Tracheal Tubes	0.15	26,843	0.005	0.053	-132	39,192	-0.002	0.028	87
Sutures	0.10	32,211	-0.020	0.040	647	29,982	0.004	0.027	-109
Polypropylene Sutures	0.07	35,403	-0.014	0.038	512	49,679	-0.013	0.021	629
Trocars	0.09	72,804	0.023	0.023	-1,658	80,086	-0.014	0.023	1,114
Suture Anchors	0.07	62,562	-0.035	0.031	2,205	98,318	0.009	0.010	-930
GI Staples	0.18	58,283	-0.064	0.144	3,728	183,210	-0.076	0.057	13,931
Electrosurgical Forceps	0.12	100,609	0.031	0.041	-3,114	155,306	-0.031	0.023	4,892
Polymeric Mesh	0.06	89,673	-0.048	0.024	4,268	148,059	0.005	0.011	-728
Bone Nails	0.07	149,845	-0.072	0.023	10,728	132,104	-0.002	0.014	239
Trauma Bone Plates	0.05	135,915	-0.032	0.009	4,401	133,282	-0.018	0.005	2,418
Surgical Staplers	0.08	161,796	0.017	0.018	-2,757	163,854	0.007	0.013	-1,153
Bone Implant Putty	0.05	207,381	0.016	0.017	-3,310	152,812	0.003	0.007	-463
Spinal Bone Plates	0.08	184,493	0.063	0.020	-11,595	153,061	-0.002	0.022	319
Guiding Cath.	0.09	201,432	-0.003	0.014	519	186,996	0.007	0.008	-1,240
Guide Wires	0.09	225,899	-0.017	0.009	3,799	247,702	-0.002	0.005	419
Trauma Bone Screws	0.08	174,039	-0.025	0.007	4,348	231,470	-0.013	0.004	3,025
Bone Grafts	0.04	275,187	-0.007	0.009	2,061	352,701	-0.009	0.005	3,208
Ablation/Mapping Catheters	0.07	491,229	-0.004	0.015	2,074	398,176	-0.019	0.007	7,596
Aortic Stents	0.03	370,289	0.012	0.024	-4,349	429,992	0.013	0.017	-5,452
Spinal Bone Screws	0.10	783,374	0.014	0.016	-11,173	716,334	0.001	0.011	-566
Other Med/Surg Total		3,912,317			1,493	4,141,220			29,687
Intraocular Lenses	0.05	85,130	0.012	0.013	-1,011	112,267	0.007	0.017	-809
Spinal Rod Implants	0.09	84,839	-0.023	0.028	1,913	78,096	0.023	0.015	-1,812
Allografts	0.05	121,461	-0.032	0.033	3,946	170,192	0.031	0.020	-5,314
Embolization Coil	0.04	126,795	0.046	0.035	-5,792	190,202	0.012	0.013	-2,221
Mammary Prosth.	0.04	198,467	-0.041	0.017	8,202	266,688	-0.007	0.008	1,851
Acetabular Hip Prosth.	0.12	212,804	-0.083	0.049	17,636	191,340	0.029	0.021	-5,594
Spinal Stimulators	0.05	514,980	0.010	0.012	-5,349	379,773	0.013	0.007	-4,911
Tibial Knee Prosth.	0.08	416,882	-0.013	0.021	5,621	305,852	-0.012	0.012	3,673
Femoral Hip Prosth.	0.10	472,522	-0.056	0.024	26,598	351,485	0.008	0.013	-2,799
Pacemakers	0.07	549,356	-0.124	0.030	67,968	481,747	0.005	0.007	-2,422
Cardiac Valve Prosth.	0.07	419,883	-0.021	0.016	8,864	440,065	0.005	0.009	-2,213
Femoral Knee Prosth.	0.07	542,193	-0.006	0.013	3,227	415,035	0.005	0.008	-2,190
Spinal Spacers	0.06	596,326	0.024	0.014	-14,526	543,893	0.020	0.009	-11,066
Cardioverter Defib.	0.05	816,792	-0.075	0.026	61,176	720,423	0.013	0.011	-9,229
Resynchronization Defib.	0.05	852,969	-0.081	0.034	69,283	719,977	0.008	0.013	-6,002
Drug Eluting Stents	0.04	1,436,850	-0.003	0.011	3,718	1,140,904	0.005	0.006	-5,956
PPIs Total		7,448,249			251,475	6,507,939			-57,013
Grand Total		12,003,226			251,515	11,462,178			2,379

Notes: Authors' calculations from PriceGuide data. Estimated savings numbers calculating by totaling expected savings across product categories as described in Appendix D. $Gini_{uh|jmy}$ presents Gini coefficient for the product category u, for prices calculated across hospitals within product-month and averaged across product-months. $\overline{spend}_u$ presents the average pre-merger spending for target and acquirer hospitals. β_u presents the merger treatment effect as estimated from equation (2) and SE presents the corresponding standard error, clustered at the hospital-brand level. $\widehat{save}_u$ denotes the estimated savings per hospital year based on β_u and the pre-merger spending levels.

Table A6: Estimated Savings Using Across-Brand Merger Effects

		Targets				Acquirers			
	$Gini_{\mathcal{C}h\|jmy}$	$\overline{spend}_{\mathcal{C}}$	$\beta_{\mathcal{C}}$	$SE_{\mathcal{C}}$	$\widehat{save}_{\mathcal{C}}$	$\overline{spend}_{\mathcal{C}}$	$\beta_{\mathcal{C}}$	$SE_{\mathcal{C}}$	$\widehat{save}_{\mathcal{C}}$
Commodities Total	0.11	642,660	0.033	0.041	-21,341	813,019	-0.064	0.023	52,086
Other Med/Surg Total	0.08	3,912,317	0.002	0.008	-8,119	4,141,220	-0.001	0.004	2,728
PPIs Total	0.06	7,448,249	-0.026	0.007	194,516	6,507,939	0.011	0.003	-74,549
Grand Total		12,003,226			165,056	11,462,178			-19,735

Notes: Authors' calculations from PriceGuide data. Estimated savings numbers calculating by totaling average yearly spending across product categories and applying treatment effect estimates from equation (1) as described in Appendix D. $Gini_{\mathcal{C}h|jmy}$ presents Gini coefficient for product class $\mathcal{C}$, for prices calculated across hospitals within product-month and averaged across product-months. $\overline{spend}_{\mathcal{C}}$ presents the average pre-merger spending for target and acquirer hospitals. $\beta_{\mathcal{C}}$ presents the merger treatment effect as estimated from equation (1) and SE presents the corresponding standard error, clustered at the hospital-brand level. $\widehat{save}_{\mathcal{C}}$ denotes the estimated savings per hospital year based on $\beta_{\mathcal{C}}$ and the pre-merger spending levels.

Table A7: Estimated Savings Using Within-Brand Merger Effects

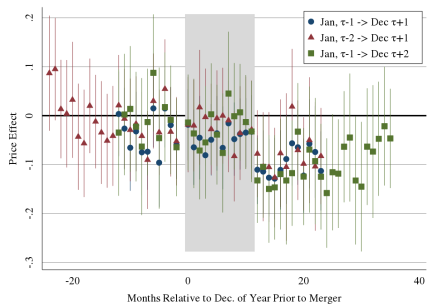
		Targets				Acquirers			
	$Gini_{\mathcal{C}h\|jmy}$	$\overline{spend}_{\mathcal{C}}$	$\beta_{\mathcal{C}}$	$SE_{\mathcal{C}}$	$\widehat{save}_{\mathcal{C}}$	$\overline{spend}_{\mathcal{C}}$	$\beta_{\mathcal{C}}$	$SE_{\mathcal{C}}$	$\widehat{save}_{\mathcal{C}}$
Commodities Total	0.11	642,660	0.003	0.022	-2,156	813,019	-0.014	0.012	11,113
Other Med/Surg Total	0.08	3,912,317	-0.005	0.005	19,898	4,141,220	-0.004	0.003	18,498
PPIs Total	0.06	7,448,249	-0.027	0.007	204,177	6,507,939	0.006	0.004	-39,228
Grand Total		12,003,226			221,919	11,462,178			-9,617

Notes: Authors' calculations from PriceGuide data. Estimated savings numbers calculating by totaling average yearly spending across product categories and applying treatment effect estimates from equation (2) as described in Appendix D. $Gini_{\mathcal{C}h|jmy}$ presents Gini coefficient for product class $\mathcal{C}$, for prices calculated across hospitals within product-month and averaged across product-months. $\overline{spend}_{\mathcal{C}}$ presents the average pre-merger spending for target and acquirer hospitals. $\beta_{\mathcal{C}}$ presents the merger treatment effect as estimated from equation (2) and SE presents the corresponding standard error, clustered at the hospital-brand level. $\widehat{save}_{\mathcal{C}}$ denotes the estimated savings per hospital year based on $\beta_{\mathcal{C}}$ and the pre-merger spending levels.

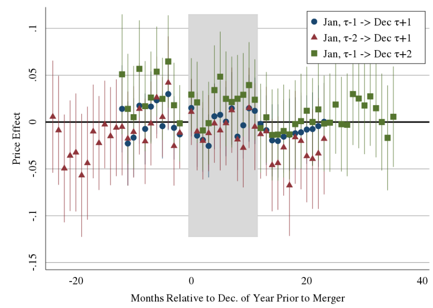
E Additional Tables and Figures

Figure A1: Merger Treatment Effects – Event Studies using Multiple Timing Supports

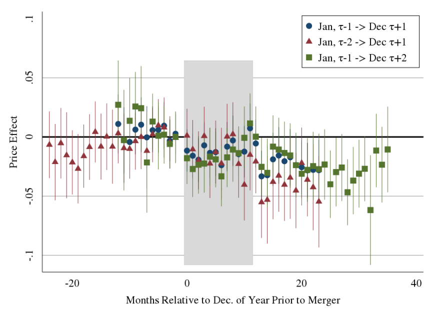
(a) Commodities, Acquirers, Eq. 1



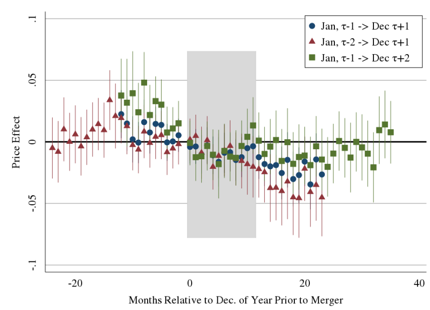
(b) Commodities, Acquirers, Eq. 2



(c) PPIs, Targets, Eq. 1

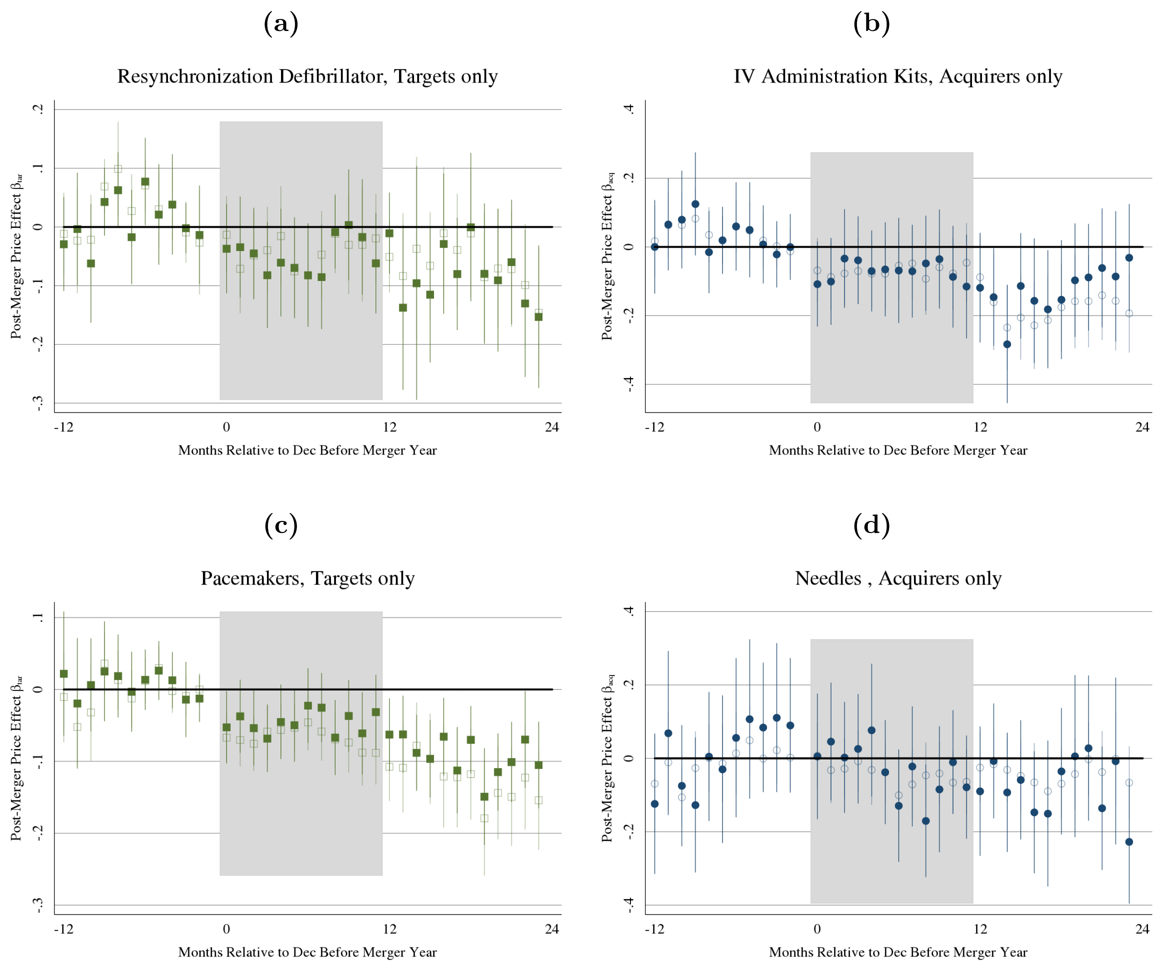


(d) PPIs, Targets, Eq. 2



Notes: Authors' calculations from PriceGuide data. Regression coefficients from pooled event study specifications, focusing on acquirers' purchase of commodities and targets' purchase of PPIs. Hold-out date is December of last pre-merger year. Bars indicate the 95% confidence interval with standard errors clustered by hospital-brand. Circles indicates the estimated series using data from the year prior to merger ($\tau_h - 1$) through the year after ($\tau_h + 1$). Triangles show estimates using data from two years prior to the merger ($\tau_h - 2$) through the year after ($\tau_h + 1$). Squares show estimates using data from one year prior to the merger ($\tau_h - 1$) through two years after the merger ($\tau_h + 2$).

Figure A2: Merger Treatment Effects – Event Studies by Product



Notes: Authors' calculations from PriceGuide data. Regression coefficients from event study version of specifications (1) and (2), each month within one year of merger year τ_h. Hold-out date is December of last pre-merger year. Standard errors clustered by hospital. Solid markers denote estimates from specification (1), which represent across-brand price effects. Hollow markers denote estimates from specification (2), representing within-brand price effects.

Table A8: Merger Treatment Effects – Pooled, Wild Bootstrap

Dependent Variable:	ln(Price)			
Commodities	0.033	0.003	-0.064†	-0.014
	(-0.030, 0.100)	(-0.028, 0.035)	(-0.099, -0.033)	(-0.032, 0.004)
Other Med/Surg	0.002	-0.005	-0.001	-0.004
	(-0.011, 0.014)	(-0.013, 0.003)	(-0.007, 0.007)	(-0.009, 0.000)
PPIs	-0.026†	-0.027†	0.011†	0.006*
	(-0.036, -0.016)	(-0.038, -0.016)	(0.007, 0.017)	(0.001, 0.012)
Fixed Effects:	$\theta_{uh} + \theta_{jym}$	$\theta_{uhj} + \theta_{jmy}$	$\theta_{uh} + \theta_{jmy}$	$\theta_{uhj} + \theta_{jmy}$
Treatment:	Targets		Acquirers	

Dependent Variable:	Standardized	
Commodities	0.010	0.019
	(-0.090, 0.109)	(-0.024, 0.072)
Other Med/Surg	-0.030	0.058**
	(-0.058, 0.042)	(-0.001, 0.069)
PPIs	-0.036	0.034
	(-0.124, 0.052)	(-0.016, 0.081)
Fixed Effects:	$\theta_{uh} + \theta_{uy}$	$\theta_{uh} + \theta_{uy}$
Treatment:	Targets	Acquirers

Notes: Authors' calculations from PriceGuide data. * $p < 0.10$, ** $p < 0.05$, † $p < 0.01$. 95% confidence intervals generated from a wild bootstrap clustered at the hospital-brand level in parentheses ($n = 1,000$). Coefficients estimated from pooled specifications (1) and (2). The dependent variable ln(Price) is the logged transaction price measured at the hospital-brand-month-year. The dependent variable in the Standardization regressions is an indicator for whether the hospital bought at least 75% of all units in a product category from a single vendor in a given calendar year. All price specifications include brand-month-year fixed-effects. Standardization coefficients are centered to indicate that the specification only includes hospital and yearly fixed-effects.

Table A9: Merger Treatment Effects – Pooled, Matched Sample

Dependent Variable:	ln(Price)			
Commodities	0.073	0.011	-0.051**	-0.027**
	(0.047)	(0.030)	(0.023)	(0.014)
Other Med/Surg	-0.009	-0.012**	0.002	-0.008**
	(0.008)	(0.005)	(0.004)	(0.003)
PPIs	-0.028†	-0.038†	0.008**	0.005
	(0.007)	(0.008)	(0.004)	(0.004)
Fixed Effects:	$\theta_{uh} + \theta_{jym}$	$\theta_{uhj} + \theta_{jmy}$	$\theta_{uh} + \theta_{jmy}$	$\theta_{uhj} + \theta_{jmy}$
Treatment:	Targets		Acquirers	

Dependent Variable:	Standardized	
Commodities	0.035	0.028
	(0.063)	(0.032)
Other Med/Surg	-0.042	0.068†
	(0.037)	(0.024)
PPIs	-0.007	0.025
	(0.049)	(0.030)
Fixed Effects:	$\theta_{uh} + \theta_{uy}$	$\theta_{uh} + \theta_{uy}$
Treatment:	Targets	Acquirers

Notes: Authors' calculations from PriceGuide data. * $p < 0.10$, ** $p < 0.05$, † $p < 0.01$. Standard errors clustered at the hospital-brand level in parentheses. Coefficients estimated from pooled specifications (1) and (2). The dependent variable ln(Price) is the logged transaction price measured at the hospital-brand-month-year. The dependent variable in the Standardization regressions is an indicator for whether the hospital bought at least 75% of all units in a product category from a single vendor in a given calendar year. Hospitals are matched to their 10 nearest neighbors using propensity scores from a probit, which models probability of merger using number of beds, Medicare and Medicaid share of discharges, teaching status, non-profit ownership, HMO penetration, and log inputs (FTEs and technologies) and outputs (admissions) as in Dranove and Lindrooth (2003). All price specifications include brand-month-year fixed-effects. Standardization coefficients are centered to indicate that the specification only includes hospital and yearly fixed-effects.

Table A10: Merger Treatment Effects – Pooled, Standardization for $Share(Q) > 0.9$

	Targets	Acquirers
Commodities		
Standardized	-0.073	-0.009
	(0.044)	(0.031)
Other Med/Surg		
Standardized	0.009	0.014
	(0.040)	(0.017)
PPIs		
Standardized	-0.033	0.031
	(0.044)	(0.022)

Notes: Authors' calculations from PriceGuide data. * $p < 0.10$, ** $p < 0.05$, † $p < 0.01$. Standard errors clustered at the hospital level in parentheses. Coefficients estimated from pooled specifications (1) with hospital and year fixed-effects. The dependent variable in the Standardization regressions is an indicator for whether the hospital bought at least 90% of all units in a product category from a single vendor in a given calendar year.

Table A11: Merger Treatment Effects – Pooled, Including Year of Merger

Dependent Variable:	ln(Price)			
Commodities	0.042	0.002	-0.033*	-0.008
	(0.032)	(0.016)	(0.019)	(0.010)
Other Med/Surg	0.002	-0.004	0.002	0.001
	(0.007)	(0.004)	(0.003)	(0.002)
PPIs	-0.019†	-0.020†	0.009†	0.006**
	(0.006)	(0.005)	(0.003)	(0.003)
Fixed Effects:	$\theta_{uh} + \theta_{jym}$	$\theta_{uhj} + \theta_{jmy}$	$\theta_{uh} + \theta_{jmy}$	$\theta_{uhj} + \theta_{jmy}$
Treatment:	Targets		Acquirers	

Dependent Variable:	Standardized	
Commodities	-0.022	0.017
	(0.051)	(0.023)
Other Med/Surg	-0.025	0.047†
	(0.031)	(0.018)
PPIs	-0.060	0.007
	(0.040)	(0.023)
Fixed Effects:	$\theta_{uh} + \theta_{uy}$	$\theta_{uh} + \theta_{uy}$
Treatment:	Targets	Acquirers

Notes: Authors' calculations from PriceGuide data. * $p < 0.10$, ** $p < 0.05$, † $p < 0.01$. Standard errors clustered at the hospital-brand level in parentheses. Coefficients estimated from pooled specifications (1) and (2) with the modification that the post-merger treatment includes the year of merger τ_h. The dependent variable ln(Price) is the logged transaction price measured at the hospital-brand-month-year. The dependent variable in the Standardization regressions is an indicator for whether the hospital bought at least 75% of all units in a product category from a single vendor in a given calendar year. All price specifications include brand-month-year fixed-effects. Standardization coefficients are centered to indicate that the specification only includes hospital and yearly fixed-effects.

Table A12: Merger Treatment Effects – Heterogeneity

	Targets					Acquirers				
		$\theta_h + \theta_{jmy}$		$\theta_{hj} + \theta_{jmy}$			$\theta_h + \theta_{jmy}$		$\theta_{hj} + \theta_{jmy}$	
	N_{tar}	β	SE	β	SE	N_{acq}	β	SE	β	SE
Commodities										
Acquirer Size										
Small	13	0.104	(0.067)	0.044	(0.045)	26	-0.037	(0.033)	-0.045**	(0.018)
Large	20	0.042	(0.053)	-0.025	(0.035)	58	-0.067**	(0.030)	-0.001	(0.019)
Market Exposure										
In HRR	14	0.077	(0.058)	0.015	(0.044)	37	-0.017	(0.028)	-0.030*	(0.017)
Out of HRR	19	0.068	(0.065)	0.005	(0.034)	47	-0.097†	(0.034)	-0.021	(0.021)
Vendor Market Structure										
High	33	0.122*	(0.068)	0.015	(0.036)	84	-0.045	(0.033)	-0.025	(0.017)
Low	33	-0.028	(0.023)	-0.007	(0.012)	84	-0.063†	(0.020)	-0.035†	(0.008)
Controlling for Output Price										
Post-Merger	33	0.111**	(0.051)	0.018	(0.032)	84	-0.046**	(0.023)	-0.028**	(0.014)
ln(Output Price)		-0.021	(0.037)	0.021	(0.017)		-0.021	(0.025)	-0.016	(0.013)
Standardization Interaction										
Post-Merger	33	0.211†	(0.074)	0.039	(0.040)	80	-0.019	(0.032)	-0.048†	(0.017)
Standardized		0.032	(0.033)	-0.016	(0.016)		-0.018	(0.021)	-0.005	(0.010)
Post X Std.		-0.262†	(0.082)	-0.069	(0.047)		-0.050	(0.039)	0.044**	(0.022)
Other Med/Surg										
Acquirer Size										
Small	13	-0.000	(0.010)	-0.010*	(0.006)	26	0.003	(0.005)	-0.009**	(0.004)
Large	20	-0.016	(0.011)	-0.015*	(0.008)	61	0.002	(0.007)	-0.005	(0.004)
Market Exposure										
In HRR	14	-0.014	(0.010)	-0.009	(0.006)	36	0.006	(0.005)	-0.011†	(0.004)
Out of HRR	19	-0.005	(0.011)	-0.015**	(0.007)	51	-0.004	(0.006)	-0.000	(0.005)
Vendor Market Structure										
High	33	-0.024*	(0.013)	-0.017†	(0.005)	87	-0.008	(0.006)	-0.010†	(0.003)
Low	33	0.003	(0.010)	-0.009	(0.008)	87	0.011*	(0.006)	-0.007	(0.005)
Controlling for Output Price										
Post-Merger	33	-0.007	(0.008)	-0.011**	(0.005)	87	0.002	(0.004)	-0.009†	(0.003)
ln(Output Price)		0.019**	(0.007)	0.016†	(0.005)		0.007*	(0.004)	0.010†	(0.003)
Standardization Interaction										
Post-Merger	29	-0.010	(0.008)	-0.018†	(0.006)	81	0.007	(0.006)	-0.003	(0.004)
Standardized		-0.014†	(0.005)	-0.008**	(0.004)		-0.016†	(0.004)	-0.002	(0.002)
Post X Std.		0.011	(0.015)	0.026†	(0.009)		-0.009	(0.008)	-0.016**	(0.006)
PPIs										
Acquirer Size										
Small	12	-0.052†	(0.012)	-0.035†	(0.011)	26	0.002	(0.005)	0.004	(0.005)
Large	17	-0.009	(0.008)	-0.041†	(0.013)	48	0.016†	(0.005)	0.006	(0.006)
Market Exposure										
In HRR	12	-0.059†	(0.011)	-0.062†	(0.013)	35	0.006	(0.004)	0.004	(0.004)
Out of HRR	17	0.004	(0.008)	-0.012	(0.009)	39	0.011**	(0.005)	0.008	(0.006)
Vendor Market Structure										
High	29	-0.027**	(0.012)	-0.042†	(0.011)	74	0.009**	(0.004)	0.006	(0.004)
Low	29	-0.028†	(0.009)	-0.036†	(0.010)	74	0.007	(0.005)	0.004	(0.005)
Controlling for Output Price										
Post-Merger	29	-0.026†	(0.007)	-0.036†	(0.008)	74	0.007**	(0.004)	0.005	(0.004)
ln(Output Price)		-0.003	(0.009)	0.023†	(0.008)		-0.008**	(0.004)	-0.014†	(0.004)
Standardization Interaction										
Post-Merger	29	-0.029†	(0.009)	-0.036†	(0.010)	67	0.007	(0.005)	0.001	(0.005)
Standardized		-0.007	(0.005)	0.004	(0.005)		-0.013†	(0.003)	0.002	(0.003)
Post X Std.		-0.004	(0.011)	-0.015	(0.011)		0.006	(0.006)	0.012*	(0.007)

Notes: Authors' calculations from PriceGuide data. * $p < 0.10$, ** $p < 0.05$, † $p < 0.01$. Standard errors clustered at the hospital-brand level in parentheses. Coefficients estimated from pooled specifications (1) and (2). The dependent variable is the logged transaction price measured at the hospital-brand-month-year. Small acquirers are hospital systems consisting of 1-3 hospitals pre-merger, and large acquirers are hospital systems with more than 3 hospitals. A target is categorized as "In HRR" if there is at least one hospital in the acquiring system in the same HRR, and vice versa. Product categories are classified as "High" concentration if its vendor HHI is above the median within its product class. ln(Output Price) is estimated using the HCRIS as in Dafny et al. (2017). Standardization is an indicator for whether the hospital purchased at least 75% of all units in a product category from a single vendor in a given calendar year.