LOBBYING PHYSICIANS: PAYMENTS FROM INDUSTRY AND HOSPITAL PROCUREMENT OF MEDICAL DEVICES*

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Abstract

We draw upon newly merged administrative data sets to study the relationship between payments from medical technology firms to physicians and medical device procurement by hospitals. These payments (and accompanying interactions) may facilitate the transfer of valuable information to and from physicians. However, they may also influence physicians' preferences, and in turn hospital device procurement, in favor of paying firms. 87 percent of device sales in our sample occurred at a hospital where a relevant physician received a payment from a device firm. Event studies suggest that, compared to synthetic controls, a large positive increase in payments to a given hospital from a given firm is associated with 27 percent higher expenditures on the paying firm's devices post-event. Controlling for patient complexity, we find no evidence that payments affect prices or total quantity of devices used, but payments are correlated with larger deviations from the procurement patterns of top Academic Medical Centers, a plausible expert benchmark. JEL No. D23,D73,I11,L15.

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1 Introduction

When procuring goods and services, large organizations generally rely on the efforts and recommendations of informed agents whose preferences may diverge from the organizations' own. In some cases, the end results are cost overruns and waste (Flyvbjerg et al., 2008; Bandiera et al., 2009). In others, the agency problem is exacerbated by selling firms influencing the agent, potentially leading to favoritism and other forms of corruption (Di Tella and Schargrodsky, 2003; Mironov and Zhuravskaya, 2016; Coviello and Gagliarducci, 2017; Lichand and Fernades, 2019). Much of the literature on public procurement has focused on organizations' efforts to mitigate these agency problems using constraints on the procurement process and on agents themselves, and has estimated the impacts of such constraints on procurement outcomes (e.g., Olken 2007; Lewis-Faupel et al. 2016; Rasul and Rogger 2018; Decarolis et al. 2020; Bandiera et al. 2021).[1] However, to our knowledge, prior researchers have not been able to directly observe interactions between selling firms and procurement agents. In this paper, we analyze hospitals' procurement of medical devices, and provide direct evidence on how key procurement outcomes covary with observed firm influence activities, focusing on firm payments to physicians who request, choose, and use the devices during hospital-based procedures.[2]

Since their inception, medical device firms have formed close relationships with the physicians who use their devices.[3] Device firm sales representatives have specialized knowledge about products, and are often physically present in the operating room for procedures, providing training on new technology and technical assistance on an ongoing basis (Bedard et al., 2014; O'Connor et al., 2016; Farmer, 2018). Firms and physicians also have interactions involving consulting, technology development, and product testing, and many impor-

[1] See Bosio et al. (2020) for a review.

[2] This empirical exercise is related to recent research on political lobbying, in which data on interested firms' interactions with policymakers is used to shed light on the benefits of information and costs of agency conflicts that may result from those interactions (Bertrand et al., 2014; Kang, 2016).

[3] Throughout this draft, we exclusively use the term "firm" to refer to a medical device manufacturer, even though the different databases we use for our analysis use the terms "manufacturer" and "vendor."

tant technologies have physician inventors (Chatterji et al., 2008). The frequent interactions observed between device representatives and physicians may embody efficient sharing of expertise and feedback. Additionally or alternatively, they may represent opportunities for device representatives to persuade physicians to use their firms' products.

While many facets of device firm-physician interactions are difficult to observe, they often involve firms providing payments and in-kind compensation, such as meals, to physicians. In this study, we analyze new data on device industry payments to physicians and their relationship with device procurement outcomes at the physicians' affiliated hospitals, across payment types and a number of important device categories. Many of the top-selling medical devices are "physician preference items," key components implanted during surgical procedures, regarding which physicians often have particularly strong brand preferences. The size of the implantable medical device market was approximately $211.3 billion over the years 2014-2017 (BMI Research, 2020; Bergman et al., 2021), and total health care spending driven by the medical device market was much larger, as it would have included reimbursement for a range of physician and hospital services associated with implantation procedures.

Our paper is novel in the procurement literature in that we focus on firms' relationships with expert intermediaries, rather than purchasing agents or public sector bureaucrats. The potential for conflicts of interest among expert intermediaries has parallels in a range of settings, including insurance, financial services, and health care (Levitt and Syverson, 2008; Schneider, 2012; Egan et al., 2019; Anagol et al., 2017; Bhattacharya et al., 2020; Egan et al., 2020; Grennan et al., 2020; Robles-Garcia, 2020). In our empirical context, hospitals are the actual device purchasers, with medical supplies representing 23 percent of hospital operating costs (Craig et al., 2021). However, physicians play a key role in procurement and are thus the primary focus of firm marketing activities: Physicians choose what device to use in each procedure, and they influence hospitals to establish contracts with their preferred vendors.[4] Physician device preferences are based on their subjective assessments of product

[4]Historically, physicians and hospitals have been organizationally and financially separate co-producers of hospital-based care (Scott et al., 2017), and physicians have had substantial control over the flow of hospital

quality, which may be influenced by firm interactions (Montgomery and Schneller, 2007), and they generally have limited awareness or consideration of costs (Okike et al., 2014). In this way, our empirical setting represents a special instance of the widely-studied phenomenon of imperfect physician agency (McGuire, 2000).

Firm payments to physicians range from meals and travel accommodations to consulting fees and royalties. In 2008-9, the Medicare Payment Advisory Commission and the Institute of Medicine flagged the aforementioned agency problem and advocated for greater transparency of and restrictions on payments from medical device and pharmaceutical firms to physicians. Since then, several states and many academic medical centers (AMCs) have significantly restricted physician-industry interactions, and the Physician Payment Sunshine Act (2010) now requires broad public disclosure of payments.[5] This attention has spurred many recent studies on pharmaceutical industry payments and drug prescribing (DeJong et al. 2016; Yeh et al. 2016; Agha and Zeltzer 2019; Grennan et al. 2020; Carey et al. 2021).[6] Far less attention has been paid to interactions between physicians and the device industry, with Smieliauskas (2016); Fujiwara et al. (2017); Annapureddy et al. (2020) being notable exceptions focused on single device categories.[7] This gap is critical, as payments from device firms to physicians are larger than payments from pharmaceutical firms in absolute magnitude, and seven times as large relative to total industry revenue. In addition to involving more dollars, device firm-physician interactions are more heavily weighted toward payments related to training and innovation (e.g., payments for continuing education and royalties) as opposed to meals, suggesting these interactions involve significantly more time and touch points than pharmaceutical firm relationships with physicians (Bergman et al., 2021). Perhaps the most important difference is that physician decisions about medical de-

admissions.

[5]For commentary, see, e.g., Rosenbaum (2015); Steinbrook et al. (2015), or the entire May 2017 issue of the *Journal of the American Medical Association*.

[6]See Mitchell et al. (2021) for a meta-analysis of thirty six studies.

[7]The closest of these studies to our own is Annapureddy et al. (2020), who found that patients were more likely to receive implantable cardioverter defibrillator (ICD) devices made by the firm that provided the highest total payment to their surgeon.

vices are an integral part of hospital procurement, with contracts for the most advanced and expensive devices typically being determined at the hospital level and involving input from both physicians and administrators. In contrast, pharmaceutical contracts are typically with insurers rather than patients or prescribers, and farther removed from individual physician prescribing decisions. For all of these reasons, we would hesitate to extrapolate findings from pharmaceuticals to the device setting.

In this paper, we combine administrative data on payments from OpenPayments.gov with administrative data on hospital purchasing from ECRI Institute. We present several new facts regarding industry payments and procurement outcomes for the top eight device categories in terms of payments, accounting for 44 percent of device-related payments within our sample and including cardiac, orthopedic, and neurosurgical devices. We also merge the above dataset with Medicare data in order to carefully control for patient complexity, an important potential factor influencing device procurement and treatment decisions.

Our first result is that, within category-hospital-firm, there are large positive associations between payments and device sales. When a hospital's affiliated physicians receive payments, or more payments, the hospital is more likely to contract with paying firms and, conditional on having a contract, purchases paying firms' devices in greater volumes. These are driven by hospitals shifting market shares across firms, rather than by expanding the total number of devices purchased or by paying higher prices. The associations are also higher for the first dollar of payments than for any incremental dollar increase in payments. At the same time, we also document evidence that within-hospital-firm relationships involve many small fluctuations in payments that introduce noise for the purpose of understanding the association between payments and procurement.

Second, when we isolate the payment variation driven by large positive shocks to payment relationships between hospitals and firms (using synthetic difference-in-differences event studies), the estimated sales-payment elasticities more than triple. In other words, large increases in payments are contemporaneous with large increases in sales. These patterns are

consistent with payments, and their accompanying interactions, having a substantial causal impact on sales. We cannot definitively rule out the possibility that both payments and sales are contemporaneously driven by unobserved time-varying factors such as unobserved taste shocks. However, we observe a roughly symmetrical pattern in post-event procurement outcomes when there are large *negative* shocks to payments. This pattern provides stronger evidence in favor of the causal mechanism, as it is less likely that unobserved factors would have symmetrical effects on *both* payments and outcomes.[8] The synthetic difference-in-difference results confirm the previous finding that payments are associated with shifts in market share, rather than market expansion or higher prices. Moreover, they are similar across a range of product categories, and are higher for the most commonly observed low-dollar meal-related payments than for relatively rare and lucrative education and consulting/speaking-related payments.

Lastly, we analyze whether payments are correlated with differences in the quality of device procurement. We use market shares of each device brand at top AMCs that do not receive substantial payments as an "expert" benchmark, under the presumption that unpaid top AMCs are where unbiased physicians with the greatest expertise regarding quality differentials across devices practice. We find that payments are correlated with greater deviations from that benchmark, suggesting that the mechanisms that mediate the payment-procurement correlations documented in this paper may push hospitals away from choosing devices optimally.

Overall, our findings highlight the important role of physician-firm interactions in hospitals' procurement of medical devices. We document a strong positive association between payments to physicians and hospitals' device procurement outcomes. This finding contributes to our understanding of the central principal-agent problem in the procurement literature by directly analyzing the pecuniary transfers from selling firms to agents, which are generally unobserved or only inferred in studies of government procurement and corruption (Bosio

[8]That is, for a confounding factor to explain the patterns we observe, its impact on sales would need to be positive when it leads to higher payments, and negative when it leads to lower payments.

et al., 2020; Decarolis et al., 2020; Bandiera et al., 2021).

Our results also shed light on mechanisms. In contrast to much of the prior literature on procurement, the associations between firm influence activities and procurement outcomes in our empirical setting load on market shares rather than on total units procured (Burgess et al., 2015) or unit prices (Coviello and Gagliarducci, 2017; Best et al., 2019; Baranek and Titl, 2020). This is perhaps reassuring evidence against the most unambiguous harbingers of waste—unnecessary procedures and overpayment. However, to the extent that there is meaningful quality variation in the product categories analyzed, our results on hospital deviations from our benchmark expert device mix suggest that payments are correlated with "worse" outcomes, in terms of the quality of the procured devices.

Finally, our results on different margins of payments clarify the nature of physician-firm relationships. We find that the strongest associations between payments and procurement outcomes are for common, low-value meals rather than more remunerative education or consulting/speaking-related payments, and that there are diminishing returns to higher payment dollar amounts. These results are particularly striking when one compares the dollar value of a meal to, say, the annual salary of a cardiac surgeon. Our findings are consistent with prior experimental research demonstrating that small gifts like those seen in our setting can be highly effective in influencing public sector procurement, and in political lobbying (Malmendier and Schmidt, 2017). Moreover, they are more consistent with payments being proxies for device firm-physician interactions, than with the simpler characterization of payments as "bribes."

The paper proceeds as follows. Section 2 summarizes our novel dataset and presents a simple conceptual framework to motivate our empirical analyses. Section 3 presents regression results regarding the associations between payments and procurement outcomes. Section 4 estimates the association between payments and deviations of device purchasing patterns from a plausible expert benchmark. Section 5 concludes with a discussion of findings and implications for future research.

2 Setting and Data

In determining which products to procure, purchasing administrators within a hospital factor in clinical value, safety, cost, and other factors. Contracting can take place directly between a hospital and a firm, or hospitals may rely on group purchasing organizations (GPOs) or other contracting coalitions to negotiate their contracts. However, GPO contracts are often used only as a starting point for direct hospital-firm negotiations for many high-cost products (Schneller, 2009). Physicians are the end users who ultimately decide what implants to use, and accordingly have an influence on which suppliers are contracted with. Physicians' brand preferences can increase hospitals' device costs directly if physicians don't choose the least-cost contracted items, and indirectly by reducing hospitals' leverage to negotiate lower prices.

2.1 Data sources

We relied on data from three main sources over 2014-2017. Our payment data are from the Centers for Medicare and Medicaid Services' (CMS') Open Payments (OP) database. The OP data contain information on all pharmaceutical and medical device industry payments made to US physicians. Each entry in the database identifies: the recipient of the payment; the firm making the payment; and the date, amount, and type of the payment. In some cases, the name of the product being promoted is also named. We followed the literature by focusing on non-research payments. Approximately $3.6 billion in non-research payments related to medical devices were made to U.S. physicians over 2014-2017.[9]

We matched OP payment recipients with providers in CMS' Medicare Provider Utilization and Payment Data. These "Medicare data" contain information on physician billing under the Medicare program, which covered 58 million elderly and disabled beneficiaries in 2017. OP payment recipients are identified by name, address, and specialty. As discussed in Appendix A, we matched payment recipients to physicians' unique National Provider Identifiers (NPIs)

[9] Analogous research payments amounted to $84 million in 2017.

in the Medicare data by name and address, recovering NPIs for 98 percent of recipients. This linkage allowed us to recover each physician's specialty, total Medicare billing, total volume of services provided to Medicare beneficiaries (in units of Medicare beneficiary-days, the number of days in which each unique Medicare beneficiary received services from the physician), and average intensity of services provided to Medicare beneficiaries (in units of "work relative value units (RVUs)" associated with physician billing codes).[10] We then linked payments in the OP data to paid physicians' affiliated hospitals using physicians' top hospital affiliations as reported in CMS' Physician Compare database.

We linked hospitals in the OP data to American Hospital Association (AHA) Annual Survey data on hospital characteristics, including the number of hospital beds, the number of full time physicians and dentists, the share of Medicare and Medicaid discharges, and whether each hospital was nonprofit, government-run, Critical Access, integrated salary model, and/or a teaching hospital. We linked each hospital to an AMC if at least 10 percent of its affiliated physicians were listed as faculty at that AMC in the Association of American Medical Colleges faculty roster. For each hospital system, we identified the highest-ranked affiliated AMC using the 2014 U.S. News & World Report ranking of medical schools. We then assigned that ranking to any general acute care, non-federal, teaching hospital within the hospital system.

Lastly, we linked the OP payments to medical device transactions in ECRI's Supply Guide data, which contain all consumable medical supply purchase orders issued by a large sample of US hospitals. We used a trusted third party, who had entered into a confidentiality agreement with ECRI, to link the OP payment variables and other hospital characteristics summarized in the paper to anonymous hospital IDs that could then be merged with the deidentified Supply Guide data. All analyses were run on this deidentified data on a secure

[10]RVUs determine the fees received for services physicians bill to Medicare and other payers. Work RVUs incorporate regulators' estimates of the intensity and effort associated with different procedures. There are also two other RVU components that adjust for differences in practice expenses and medical liability insurance associated with different services. To convert RVUs into dollars, the (geographically adjusted) sum of the three different RVU components is multiplied by a common conversion factor; in 2014, the conversion factor was approximately $35.83 per RVU (Chan and Dickstein, 2019).

server, and only aggregate statistics and regression coefficients were extracted by researchers.

For each transaction, we observed price, quantity, month, item description, manufacturer, and a product category based on ECRI's "Universal Medical Device Nomenclature System (UMDNS)." The UMDNS system classifies medical supplies based on intended purpose, with some distinctions for mechanism of action. For example, drug-eluting coronary stents have UMDNS code 20383.

We matched each payment in the OP data to firms and UMDNS codes in the Supply Guide data. In the OP data, devices were only identified by free-form text fields. These fields were filled by the firm submitting the payment information, and varied significantly in specificity across firm-years. Some entries in this field described a range of products rather than a single brand, or referred to the whole range of devices produced by the firm.

Our matching methodology is described in detail in Appendix A. Briefly, we manually matched the top-paid items, comprising 56 percent of the dollar value of device-related non-research payments to individual physicians, and used string-matching algorithms for the remaining payments (27 percent of OP dollars). Manual inspection of unmatched payments (16 percent of OP dollars) suggested that unmatched products were typically types of medical supplies not captured in Supply Guide.[11]

2.2 Focal device categories

We focused our attention on eight top product categories, with a category average of $5.1 million in associated payments during 2014-2017. These include three cardiovascular products and five orthopedic products. The cardiovascular products are[12] **AAA** stent grafts, which are used in endovascular repair of abdominal aortic aneurysms; **atherectomy** catheters, which are used to remove plaque from large blood vessels; and **DES** coronary stents, which are

[11] We manually reviewed all unmatched items with over $1 million in associated payments in 2014-2017. 82 percent of these unmatched payment dollars were related to instruments and equipment not captured in Supply Guide, like Zoll's wearable defibrillator LifeVest; or capital equipment, like Hologic's SecurView breast imaging workstations.

[12] We highlight our preferred abbreviation for each category in bold.

small tubes placed in blocked coronary arteries during angioplasty procedures. The orthopedic products are three types of joint prostheses (**knee**, **hip**, and **shoulder**); spinal **screws**, which are used for spinal fixation; and spinal **spacers**, implants which increase vertebral height to relieve pressure on the spinal cord and nerves. Overall, these device categories accounted for $1,169 million in payments, comprising 44 percent of Supply Guide-linked general payments to individual physicians, over 2014-2017.

In each category, we focused on payments from firms to affiliated physicians whose specialties imply they are "relevant" to the device category. A specialty is "relevant" to a device category if physicians with that specialty accounted for 10 percent or more of the physician billing submitted to Medicare for procedures that employ products in the device category.[13] On average, physicians in "relevant" specialties for an included device category accounted for 90 percent of Medicare billing in related procedure codes for the device category, and for 83 percent of payments promoting products in the device category.

2.3 Summary statistics

Of the full set of 4,492 hospitals whose affiliated physicians received payments during 2014-2017, 3,235 hospitals' relevant affiliated physicians received payments from firms selling our focal device categories. We analyzed data for 933 hospitals observed to purchase devices in our focal categories in the Supply Guide data, that were matched to physicians in relevant specialties in the Medicare data. Appendix Table A6 summarizes hospitals appearing in each of these samples. Briefly, while our analytic sample includes a wide range of hospitals of the types seen in the full US sample, the hospitals in our analytic sample were larger on average, more often nonprofit, less often government-owned, less often rural or critical access hospitals, and more often teaching hospitals. Depending on the extent to which the results we document are heterogeneous across hospitals, our findings may not generalize

[13]For example, 36 percent of bills for "Insertion or repositioning of electrode lead(s) for single or dual chamber pacing cardioverter-defibrillator and insertion of pulse generator," which involves implantation of ICDs, were submitted by cardiologists. See Appendix A for further details on included device categories.

to all US hospitals whose affiliated physicians received payments. However, our sample of hospitals linked between the OP and Supply Guide data covered 38 percent of total device firm payments to US hospitals, and is therefore an important sample in its own right.

Table 1 summarizes the distribution of OP payments, hospital procurement outcomes, and select hospital characteristics in our analytic sample of linked OP and Supply Guide data, weighting each of the eight focal device categories equally so that each of the statistics below should be interpreted as applying *within the average focal device category*. We show summary statistics for all hospital-periods, where each period is a half-year ranging from the first half of 2014 to the second half of 2017, and separately for hospital-periods at different positions in the payment distribution. For the latter exercise, we group hospital-periods into three bins based on total payments (across all firms) per relevant physician, and present summary statistics for each bin in a separate column.[14]

As shown in the top panel of Table 1, we analyzed payments and utilization for 727 hospitals in the average device category and 70 percent of hospital-periods had affiliated physicians receiving some payments.[15] The next set of rows summarizes the intensive and extensive margin payment variables used in our regression analyses. Using the same notation as in our regression specifications, the variable Pay_{chft} represents the total dollar value of payments from firm f promoting products in device category c to relevant physicians in hospital h in period t, normalized by the count of relevant physicians for triplet cht. The analytic sample in each device category includes an observation for each hospital-period with positive sales in the category, crossed with each firm with at least 2 percent market share in the category.[16] This implies that there are (many) category-hospital-firm-periods with zero payments and/or zero sales. 31 percent of hospital-firm-period relationships involved payments, but this rate ranged from 33 percent in low-payment hospital-periods (at or below $40 per relevant physician) to 51 percent in high-payment hospital-periods (above $40). More

[14] Bin cutoffs are set at $0 and $40. We chose the $40 cutoff as an approximation to the median value of payments per relevant physician, conditional on receiving payment, in our sample ($41).

[15] Hospitals could appear in different payment bins in different periods.

[16] The total market share of excluded small firms was 6.4 percent in the average category.

Table 1: Payments, Procurement Outcomes, and Hospital Characteristics

			$ per relevant physician (range)		
		All hospitals	[0]	$(0, 40]$	$40 <$
Hospital count		727	426	515	469
Hospital-period count		4,187	1,236	1,464	1,488
Observations		22,700	6,887	8,144	7,669
Physician Payments					
All	$1[Pay_{chft} > 0]$ (%)	31	0	33	51
	$Pay_{chft}\|Pay_{chft} > 0$ ($)	190		9	263
		(979)		(9)	(1,103)
Meal	$1[Pay_{chft} > 0]$ (%)	29	0	31	48
	$Pay_{chft}\|Pay_{chft} > 0$ ($)	29		7	33
		(78)		(8)	(78)
Educ	$1[Pay_{chft} > 0]$ (%)	11	0	6	26
	$Pay_{chft}\|Pay_{chft} > 0$ ($)	144		8	142
		(783)		(9)	(686)
CHS	$1[Pay_{chft} > 0]$ (%)	5	0	1	12
	$Pay_{chft}\|Pay_{chft} > 0$ ($)	714		12	670
		(1,751)		(10)	(1,669)
Devices Purchases					
$1[Sales_{chft} > 0]$ (%)		48	37	49	56
$Sales_{chft}\|Sales_{chft} > 0$ ($)		10,693	10,702	8,932	11,516
		(38,181)	(47,607)	(27,995)	(35,369)
$Price_{chft}$ ($)		2,327	2,272	2,313	2,357
		(1,973)	(1,929)	(1,964)	(1,979)
Q_{cht}		30	30	26	33
		(66)	(80)	(54)	(63)
Top firm share (%)		75	83	74	70
		(21)	(19)	(20)	(20)
Other Hospital Characteristics					
Num. of relevant physicians		9	5	9	12
		(9)	(4)	(7)	(11)
Beds		338	232	346	414
		(255)	(179)	(240)	(284)
% Medicare		46	47	46	45
		(10)	(10)	(9)	(10)
% Medicaid		21	22	21	21
		(10)	(12)	(10)	(10)
Nonprofit (%)		82	81	83	82
Government (%)		12	11	12	13
Teaching (%)		53	39	53	63
Top AMC (%)		13	8	11	18

Notes: Bins are defined by payments per physician across all firms, at the category-hospital-period level. All statistics are averaged across device categories, weighting each category equally. Pay_{chft} and $Sales_{chft}$ are average payments and sales per physician, respectively, at the category-hospital-firm-period level. Standard deviations of continuous variables shown in parentheses. Device payments and purchasing statistics are from authors' calculations using Open Payments and Supply Guide data, respectively.

strikingly, the average payment per physician for hospital-periods with nonzero payments was $190 across all hospital-periods, but this varied from $9 in low-payment hospital-periods to $263 in high-payment hospital-periods, with a long right tail in high-payment hospital-periods, as suggested by the $1,103 standard deviation. As shown in Appendix Table A7, the lowest average payments to sample hospitals were related to atherectomy devices (about $65 per hospital-firm-period), and the highest average payments were related to knee implants (about $296 per hospital-firm-period).

As discussed in Bergman et al. (2021), non-research payments by medical device firms to physicians fall under several types. The most important of these are: in-kind compensation in the form of meals ("Meal"); compensation for training and continuing education, and related travel ("Educ"); and consulting fees, honoraria, and speaking fees ("CHS"). Importantly, we exclude royalty, licensing, and investment payments related to product development relationships from our analysis due their unique nature. This exclusion does not qualitatively change our results. As we look down the rows of Table 1 from "Meal" to "Educ" to "CHS," the rate of hospitals receiving each type of payment from a selling firm decreases steadily (from 29 percent for meals, to 5 percent for CHS) and the dollar value per *paid* hospital increases dramatically (from $29 per physician for meals to $714 per physician for CHS). The high-payment hospital-periods were those receiving rare, but highly lucrative CHS payments, and the more common and low-value meal payments contributed little to the heavy tail of the payments distribution.

The third panel of Table 1 breaks down the details regarding hospital purchasing of our eight focal device categories, summarizing the intensive and extensive margin sales variables used in our regression analyses. $Sales_{chft}$ and Q_{chft} are expenditures made and units purchased, respectively, in combination $chft$, normalized by the count of relevant physicians in combination cht. $Price_{chft}$ is the weighted average unit price for firm f's products in combination cht; by definition, $Price_{chft}$ is only defined if $Q_{chft} > 0$.

On average, 48 percent of included hospital-firm-periods had positive sales (i.e., an ob-

served contracting relationship). That is, hospitals tended to have more contracted firms in a given category than payment relationships. Conditional on being positive, average annual sales were $10,693. These contracting relationships were for high-priced devices used in specialized procedures; hence, the average quantity sold per hospital-period was only 30 units per physician and the average unit price was $2,327. Price variability is substantial, with the standard deviation being nearly equal to the mean across all bins of the payment distribution.

The average firm had a market share Q_{chft}/Q_{cht} of 21 percent, including firms with a market share of zero. While hospitals generally bought devices from multiple firms, hospitals tended to have a "favorite" firm. In the average category, the top seller in a hospital-period had an average market share of 75 percent.

The bottom panel of Table 1 presents details on what types of hospitals received payments, or particularly high payments. The average sample hospital-period had 9 affiliated relevant physicians, had 338 hospital beds, and was a nonprofit teaching hospital. High-payment hospitals tended to be larger, with more relevant physicians and more hospital beds. Payer mix didn't vary across hospital-periods by receipt of payments, but highly-paid hospitals were more likely to be teaching hospitals or even affiliates of top AMCs. This is consistent with CHS payments being more heavily weighted toward top tier research hospitals.

Our regression control set includes, at the hospital-category-year level: (1) the number of physicians in specialties for which the device category is relevant ("category physicians"), logged; (2) the total Medicare Part B billing by category physicians from CMS data, logged; (3) the average category physician's number of Medicare Part B beneficiaries per physician-service, weighted by service volume, logged; and (4) the average category physician's work RVU for Medicare Part B services, weighted by service volume, logged. Additional controls are at the hospital-year level: (5) the number of full time physicians and dentists, logged; (6) the share of Medicaid discharges; (7) the share of Medicare discharges; and (8)

an indicator for an integrated salary model hospital. Hospitals' governance structure (for-profit, government), teaching status, and AMC affiliation are controlled for by the hospital-category/hospital-category-firm fixed effects terms included in the regression. See Appendix Table A10 for summary statistics.

2.4 A Model of Payments and Device Procurement

Before moving forward with the empirical analysis, we present a simple model of device procurement and payments in order to illustrate how payments may impact the various dependent variables we study and to clarify the underlying assumptions of our empirical specification. Consider a model of device choice as in Grennan (2013, 2014), modified to allow for payments and for the possibility that physicians may be imperfectly informed and/or imperfect agents for their patients as in Grennan et al. (2020). The physician treating patient i chooses device j from among the set of contracted devices $\mathcal{J}$ available at the hospital to maximize the indirect choice utility function

$$u_{ij} = \theta_j - \alpha \cdot price_j + f_i(\vec{pay}_j) + \eta_{ij}^{de} + \varepsilon_{ij}.$$

In this choice environment, the outside option is a non-device treatment relevant to that device category. For example, in the case of knee implants, the outside good would be a composite of knee prosthesis alternatives such as weight loss, physical therapy, pain medication, injections, cartilage regeneration, and radiofrequency ablation (Johns Hopkins Medicine, 2021). For each device $j \in \mathcal{J}$, θ_j represents the true average quality of the device; α measures the extent to which the physician takes into account the price $price_j$ paid by the hospital; and ε_{ij} represents the unobservable match value for the device with this particular patient. All of the above variables affect both choice utility and also real, welfare-relevant utility. However, in the spirit of Baicker et al. (2015), the other two variables enter choice utility but do not affect welfare directly: η_{ij}^{de} measures the unobservable extent to which

the physician might make systematic decision errors in matching this patient and device; $f_i(\vec{pay}_j)$ maps from the vector of payment amounts and types (meals, training, etc.) into the physician choice for this patient.

While we expect payments might directly affect choice patterns, the "physician chooses, hospital pays" nature of these surgical devices indicates that payments could also affect device pricing. Suppose without loss of generality that marginal costs of device production and distribution are zero. In that case, the model of device procurement negotiations in Grennan and Swanson (2020) would represent prices as

$$price_j = \beta_j AV_j(\{u_{ij}\}_{i \in h}; \mathcal{J})$$

where $AV_j(\{u_{ij}\}_{i \in h}; \mathcal{J})$ models the expected added value of product j to the set $\mathcal{J}$ with which the hospital h contracts and $\beta_j \in [0, 1]$ models the bargaining ability of the manufacturer vis-a-vis the hospital in capturing that value. The extent to which payments impact price will then depend on both the nature of $f_i(\vec{pay}_j)$ and also how $AV_j(\cdot)$ maps that into the pricing process, in particular whether the administrator who negotiates prices can distinguish any choice distortions from welfare relevant utility.

Exploring the nature of payments amounts to exploring the nature of $f_i(\vec{pay}_j)$ and η_{ij}^{de}. For example, $f_i(\vec{pay}_j) = -\eta_{ij}^{de}$ would model a case where payments proxy for information and activities that help correct errors that the physician might make absent the payments and interactions that payments proxy for. On the other hand, $\eta_{ij}^{de} = 0$ in combination with $f_i(\vec{pay}_j) = \delta \sum_k pay_{jk}$ would model a case where all payment dollars influence the doctor's decisions, increasing the propensity to choose the device at the rate $\delta > 0$.[17] Of course, the correct model of payments could be a hybrid of these cases. The goal of the rest of the paper is to bring empirical evidence to bear on the nature of $f_i(\vec{pay}_j)$ and its relationship with several key dependent variables: device choice, which reflects physicians' preferences

[17] Omitting the error terms, this model is analogous to the agent's problem in competitive procurement with corruption described in Burguet and Che (2004), where $\delta \sum_k pay_{jk}$ represents the agent's manipulation of the value of option j given bribes of value $\sum_k pay_{jk}$.

across promoted and non-promoted devices as in the above discrete choice model; total device quantity, which reflects physicians' preferences over procedures using the focal device vs. the outside option; device price, which reflects the influence of physicians' preferences on hospital-firm price negotiations; and, putting the previous elements together, device spending.

The above model also highlights two key challenges to research in this setting, each driven by the fact that we do not observe $\eta_{ij}^{de} + \varepsilon_{ij}$, the combination of real and perceived match value between device j and patient i. First, payments are not randomly allocated across physicians, creating an identification challenge. For example, firms may target payments to physicians based on their signals of $\eta_{ij}^{de}+\varepsilon_{ij}$. In our regression analyses in Section 3, we discuss how such selection might introduce bias and relate that potential for bias to our estimates in several specifications with a range of controls for unobserved physician preferences. Second, the presence of potential decision errors η_{ij}^{de} means that an unbiased estimate of $f_i(p\vec{a}y_j)$ may not automatically translate into welfare implications—payments may counteract, correct, or reinforce underlying decision errors. In Section 4, we present evidence on the relationship between payments and utilization relative to our best approximation of an optimal device mix, where arguably the decision error η_{ij}^{de} is minimized.

3 Payment Shocks and Device Spending

This Section analyzes how payment shocks affect device procurement outcomes. We begin with two-way fixed effects regressions that control for several dimensions of unobserved heterogeneity and explore different mechanisms and margins through which payments may influence procurement. However, as noted previously, nonrandom selection of physicians into receiving payments presents a challenge for identifying causal effects. To better address this challenge, we then turn to synthetic difference-in-differences event studies that let us isolate the impact of discrete changes in payment relationships between hospitals and firms.

Our regressions explore the relationship between the variables $1[Pay_{chft} > 0]$ and $\log(Pay_{chft})$

(characterizing the extensive margin and intensive margin, respectively, of payments from firm f to relevant physicians affiliated with hospital h in period t) and several alternative device procurement outcome variables y_{chft} for the same level of observation, controlling for covariates X_{chft}.[18] We further control for any strategic response by competitors (in the form of payments) by controlling for the variables $1[Pay_{cht,\text{-}f} > 0]$ and $\log(Pay_{cht,\text{-}f})$, the extensive and intensive margin of payments made by other firms. Finally, we control for two sets of fixed effects. Device category-hospital-firm fixed effects η_{chf} account for the time-invariant component of unobserved hospital-firm factors that impact procurement, such as policy environment, patient population and severity, and established contracting relationships and physician brand preferences, while category-firm-period fixed effects θ_{cft} account for our observing different points in the life cycles of different brands in our dataset, and for device category dummies interacted with all hospital characteristics summarized in Section 2.1 above.

We estimate these relationships separately within each device category c and pooled, weighting each category equally. We present pooled results in the main text and category-by-category results in the Appendix. The pooled regression specification is:

$$\begin{aligned} y_{chft} =& \delta^e 1[Pay_{chft} > 0] + \delta^i \log(Pay_{chft}) + \gamma^e 1[Pay_{cht,\text{-}f} > 0] \\ &+ \gamma^i \log(Pay_{cht,\text{-}f}) + X_{chft} * \beta + \eta_{chf} + \theta_{cft} + \epsilon_{chft} \end{aligned} \tag{1}$$

Table 2 summarizes the results of these regressions. The main threat to a causal interpretation of these conditional correlations will be the extent to which specific firms dynamically target payments to physicians at hospitals that would, absent payments, have relatively high (positive bias) or low (negative bias) preference for those firms' products. Payments proxying for already strong relationships with frequent users would be an example of the former, while providing payments to infrequent users as a part of an inducement strategy would be an example of the latter.

[18] We set $\log(Pay_{chft}) = 0$ if $Pay_{chft} = 0$.

Table 2: Association Between Physician Payments and Hospital Procurement

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	$1[Sales_{chft} > 0]$	$\log(Sales_{chft})$	$\log(Price_{chft})$	Q_{chft}/Q_{cht}	$\log(Q_{cht})$
$1[Pay_{chft} > 0]$	0.026**	0.041**	0.000	0.007**	-0.002
	(0.004)	(0.012)	(0.004)	(0.002)	(0.007)
$\log(Pay_{chft})$	0.004**	0.022**	0.002	0.004**	0.003
	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)
Observations	181,602	76,224	76,224	161,093	161,093
R-squared	0.673	0.830	0.922	0.828	0.858
Dependent variable mean	0.480	8.498	7.429	0.207	2.392
	(0.500)	(1.858)	(0.842)	(0.310)	(1.657)

Notes: Authors' calculations using Open Payments and Supply Guide data. Extensive and intensive margin Pay_{chft} coefficient estimates based on the model presented in equation (1). Each column presents the results of a different regression for a specific dependent variable. Observations are weighted by the inverse of the device category frequency, so that each device category receives equal weight in the regression. Standard errors clustered by firm-hospital-category in parentheses. ** p<0.01, * p<0.05.

These results suggest that payments are mainly associated with shifts in market share (business stealing), rather than with higher negotiated prices as has been highlighted in the "corruption in procurement" literature (Coviello and Gagliarducci, 2017; Best et al., 2019; Baranek and Titl, 2020), or with increased volumes of (potentially unnecessary) procedures of the type highlighted in the popular press (Schulte and Lucas, 2021). Appendix Table A8 repeats the analysis presented in Table 2, when aggregating payments and sales from the category-firm-hospital level to the category-hospital level. Similarly to our main results, we find no effect of aggregate payments on average price or total quantities purchased at the category-hospital level.

The lack of correlation between payments and prices could suggest that administrators who negotiate prices do not take the component of physicians' decision utility that is correlated with payments into account in their calculations of device added value. To the extent that hospital administrators are themselves informed regarding the quality tradeoffs associated with different devices, this would be indirect evidence against the idea that payments

correct physician decision errors.

Overall, the results of the above analyses suggest that the relationship between payments and device spending at the firm-hospital-period level is nontrivial. This relationship holds both for adding new firms to the set from which the hospital purchases and for spending conditional on being in that set. The relationship also has diminishing returns—it is usually found to be largest for the first payment dollar.

3.1 Payment Shocks

The above regressions are essentially two-way fixed effects (TWFE) specifications within each device category, but with pooled coefficients on $1[Pay_{chft} > 0]$ and $log(Pay_{chft})$. They suggest that, within a hospital-firm-category, periods with higher device-related payments were associated with higher device spending. However, device firm relationships with physicians tend to be persistent, suggesting that the above regressions may be identified in part by small fluctuations in payments within the context of a stable firm-hospital relationship. If relationships between payments and procurement outcomes depend on the magnitude of the payment "shock," or if minor fluctuations in payments for a given firm-hospital pair represent noise rather than systematic variations in hospital-firm interaction, then our above coefficient estimates would be subject to attenuation bias.

In order to shed light on this question, we next focus on discrete events where hospitals' payments jumped from low to high levels, and inversely from high to low levels.[19] An event is defined as follows. Hospital h' experienced a payment event from firm f' in category c and half-year τ within the window $[\tau - t_{pre}, \tau + t_{post}]$ if: we observed payment and utilization data for triplet $ch'f'$ throughout $[\tau - t_{pre}, \tau + t_{post}]$; average pre-event payments for $ch'f'$ were in

[19] These examples relate to the fundamental issue that there may be no single "treatment effect" of payments on procurement outcomes. For example, treatment effects may be heterogeneous across physicians, and the short-run effect of fluctuations in payments in an existing physician-firm relationship may differ from the steady state effect of a persistent physician-firm relationship with repeated interactions (Grennan et al., 2020). However, payment "events" of the kind we study below, and the types of providers that experience them, may be of particular interest for understanding what happens to hospitals' procurement when there is a large, salient shock to firm interactions.

the bottom half of the payment distribution across hospital-firm-periods in category c:

$$\left(\frac{1}{t_{pre}} \sum_{t'=\tau-t_{pre}}^{\tau-1} Pay_{ch'f't'} < P_{50\%}(Pay_{chft} | Pay_{chft} > 0) \right);$$

and average post-event payments were in the upper half of the payment distribution:

$$\left(\frac{1}{t_{post}+1} \sum_{t'=\tau}^{\tau+t_{post}} Pay_{ch'f't'} > P_{50\%}(Pay_{chft} | Pay_{chft} > 0) \right).$$

If triplet $ch'f'$ experienced multiple events, we keep only the first in the regression sample.

The above parameters define our treated category-hospital-firms. A control category-hospital is any ch' such that: h' never experiences an event; and $max_{f't'}\{Pay_{ch'f't'}\} < P_{50\%}(Pay_{chft} | Pay_{chft} > 0)$. We include all firms within each control category-hospital in the regression sample.

We estimate the impact of payment events on procurement outcomes using a synthetic difference-in-difference (SDID) model (Arkhangelsky et al., 2021). This approach combines elements of both difference-in-differences and synthetic control methods, offering a flexible framework for causal inference with panel data. The SDID estimator is implemented as a weighted two-way fixed effects regression (for ease of notation, let i index a category-hospital-firm):

$$(\hat{\tau}sdid, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \arg\min \tau, \mu, \alpha, \beta \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{\omega} i^{sdid} \hat{\lambda} t^{sdid}$$

where Y_{it} is the outcome for unit i at time t, W_{it} is the treatment indicator, α_i and β_t are unit and time fixed effects, and $\hat{\omega} i^{sdid}$ and $\hat{\lambda} t^{sdid}$ are unit and time weights respectively. These weights are chosen to balance pre-treatment trends between treated and control units, as well as pre and post-treatment periods for control units. The method allows for heterogeneous treatment effects and uses both unit and time reweighting along with two-way fixed effects to reduce bias from unobserved confounders. Under certain conditions specified in Arkhangel-

sky et al. (2021), including requirements on sample sizes and the systematic component of outcomes, the estimator is shown to be asymptotically normal.

We estimate the effect of payment increase events for several different dependent variables: We show Pay_{chft} to give a sense of the magnitude of the payment shocks; $1[Sales_{chft} > 0]$ and $\log(Sales_{chft} + 1)$ show the direct impact of payments on sales value, where we now use $\log(Sales_{chft} + 1)$ to account for both the extensive and intensive margins of sales;[20] finally, we analyze other dependent variables from our previous analyses Q_{chft}/Q_{cht}, $\log(Price_{chft})$, and $\log(Q_{cht})$. We control for competitors' strategic responses using $1[Pay_{cht,\text{-}f} > 0]$ and $\log(Pay_{cht,\text{-}f})$, as well as device category dummies.

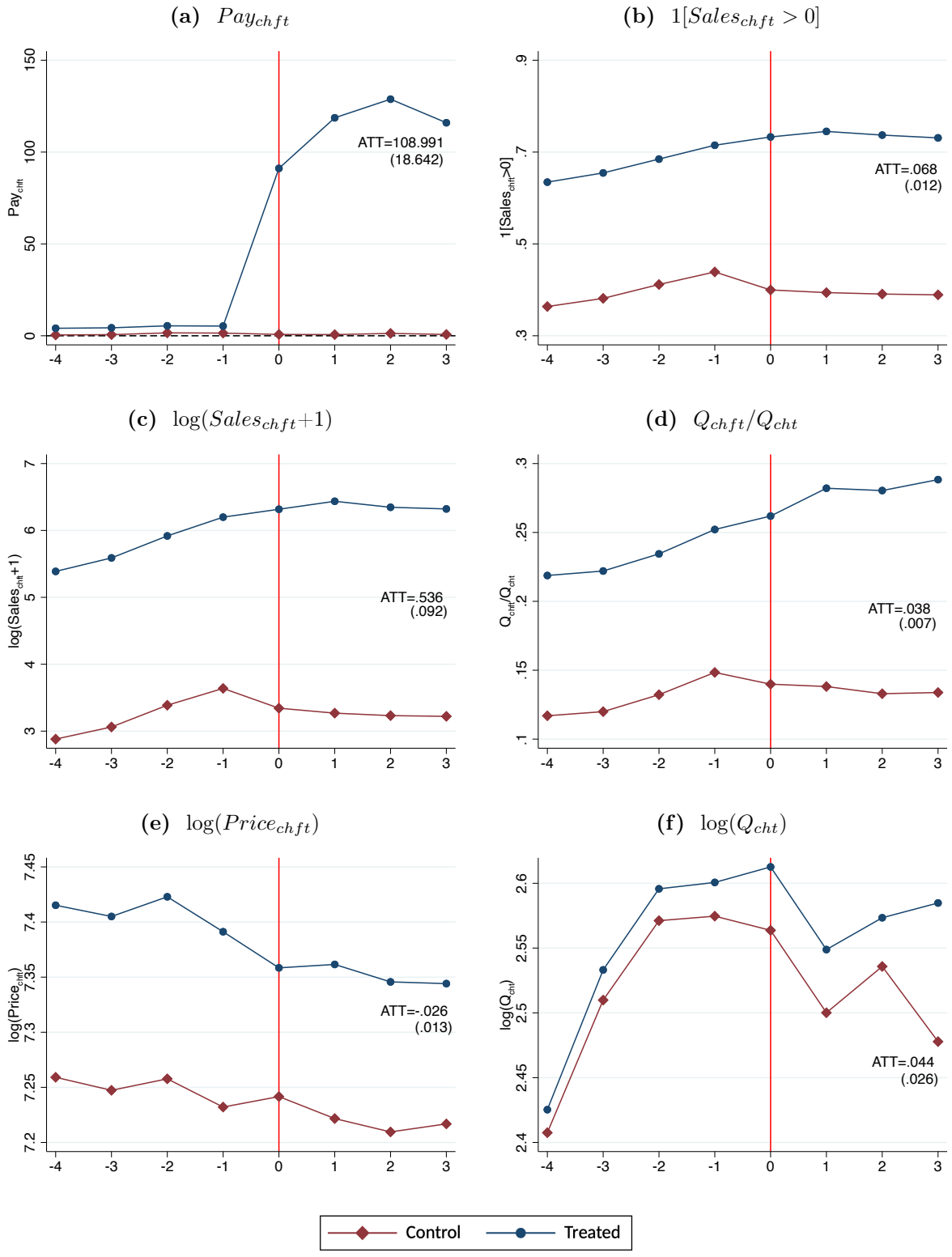
In Figure 1, we focus on payment shocks taking place in the second half of 2015, so that we have two full years of pre- and post-event data. Focusing first on the first stage estimates (Panel (a)), we see that the average event was associated with a 109 dollar increase in Pay_{chft}. Trends in payments were relatively flat within both the pre- and post-periods, suggesting that the event itself represented the most meaningful variation in payments within each window.

Next, consider the reduced form relationships between payment shocks and device sales (Panels (b) and (c)). The event studies indicate that, relative to pre-event averages and to control hospitals, event hospitals were 6.8 percentage points more likely to purchase the event firm's devices post-event and spent 50 percent more on event firm devices post-event. The increase in sales translates to a larger market share for the event firm, which was 3.8 percentage points higher, on average, post-event. Similar to our TWFE analysis, we find no statistically significant impact of payment events on either (log) price or (log) total quantity.

We contrast these increase payment events with *decrease* payment events. We define a decrease payment events analogously to the increase payment events defined above. Hospital h' experienced a decrease payment event from firm f' in category c and half-year τ within the window $[\tau - t_{pre}, \tau + t_{post}]$ if we observed payment and utilization data for

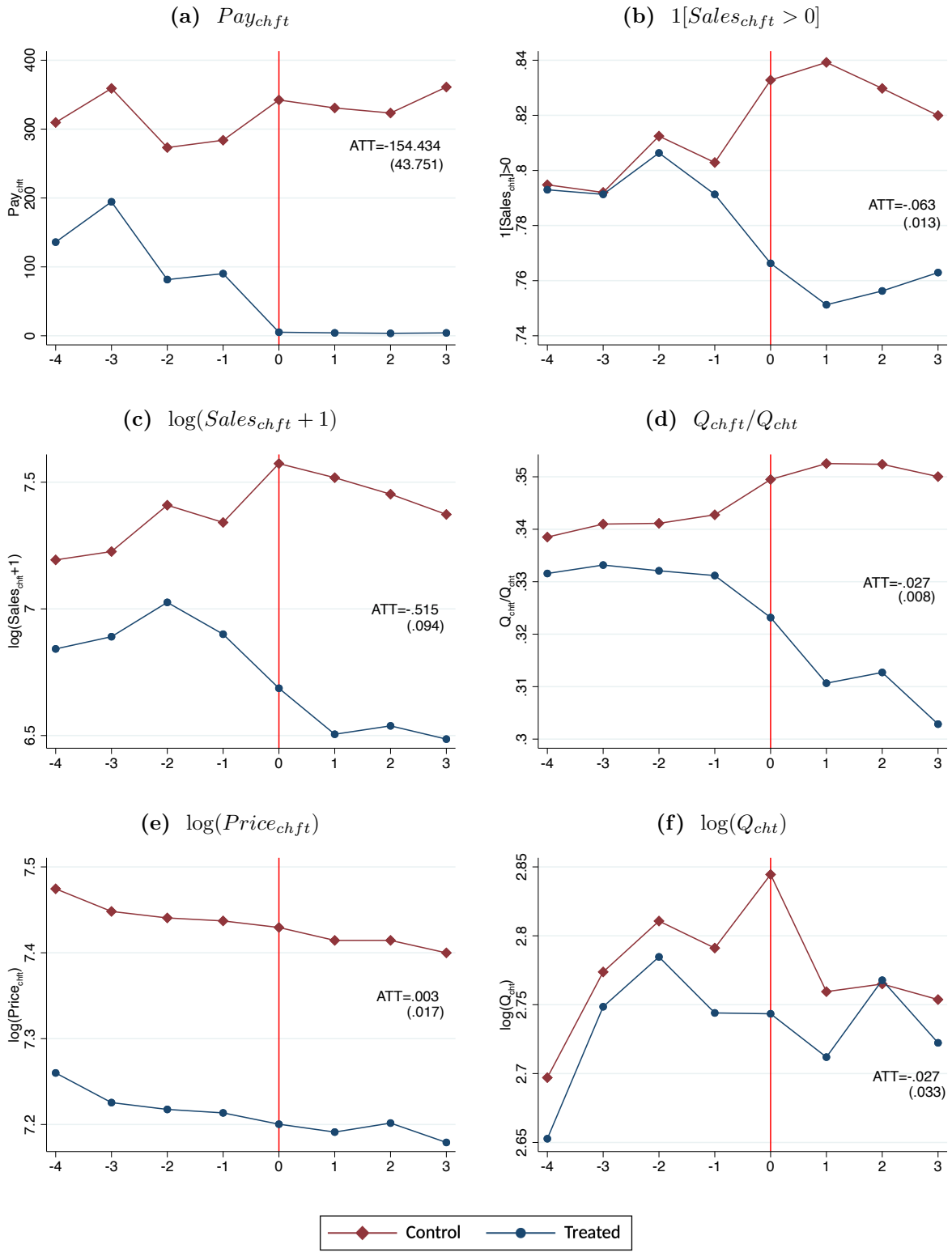
[20] Since the SDID model requires full panels for estimation, using $\log(Sales)$ would limit us to panels characterized by nonnegative sales in every period in our sample, of which there are few.

Figure 1: Event Study: Payment Increase Events



Notes: Authors' calculations using Open Payments and Supply Guide data. The x-axis denotes event time in periods, defined relative to the period of the hospital-category-specific payment shock. The analysis samples include 32,608 observations (7,848 observations for the $\log(Pricechft)$ and $\log(Qcht)$ outcome variables).

Figure 2: Event Study: Payment Decrease Events



Notes: Authors' calculations using Open Payments and Supply Guide data. The x-axis denotes event time in periods, defined relative to the period of the hospital-category-specific payment shock. The analysis samples include 13,176 observations (7,856 observations for the $\log(Pricechft)$ and $\log(Qcht)$ outcome variables).

triplet $ch'f'$ throughout $[\tau - t_{pre}, \tau + t_{post}]$; average pre-event payments for $ch'f'$ were in the upper half of the payment distribution across hospital-firm-periods in category c; and average post-event payments were in the lower half of the payment distribution. A control category-hospital is now defined as any ch' such that: h' never experiences an event; and $\frac{1}{t_{pre}+t_{post}} \sum_{t'=\tau-t_{pre}}^{t_{post}} Pay_{ch'f't'} > P_{66.7\%}(Pay_{chft}|Pay_{chft} > 0)$.

Figure 2 presents our synthetic difference-in-difference results for payment decrease events. In Panel (a), we see that the average decrease event is associated with a 154 dollar decrease in the value of payments received from the firm. Decrease in payments is accompanied by a decline in sales, as seen in Panels (b) and (c). The probability of procuring any device from the firm decreases by 6.3 percentage points post-event, and the value of sales from the event drops by 51 percent. As in the case of increase events, the change in sales volume translates to a 2.7 percentage point smaller market share for the event firm. Finally, we find no effect of decrease events on device prices or total quantities at the event hospitals, mirroring our findings from both increase event studies and our TWFE analysis.

Payment events can be driven by different types of payments—meals; education; or consulting, honoraria, and speaking (C/H/S) payments. We now turn to analyzing the effect of type-specific events. Figure 3 describes the effect of payment events on Q_{chft}/Q_{cht}, the paying firm's market share in the hospital, when events are defined by increases or decreases in payments of different types. We maintain the definition of an "increase" or "decrease" in payments remains as described above, as well as the set of controls used in the SDID estimation.

For ease of comparison, effect estimates for "decrease" events are flipped in sign in both panels of Figure 3. The left hand side panel shows how events vary in size, in dollar per physician terms, when different types of payments are studied.

Thus, interestingly, the payment dimension where devices most diverge from pharmaceuticals—larger and more prevalent payments for training, consulting, etc.—does not seem to be a quantitatively important driver of the relationship between device payments and device

spending.

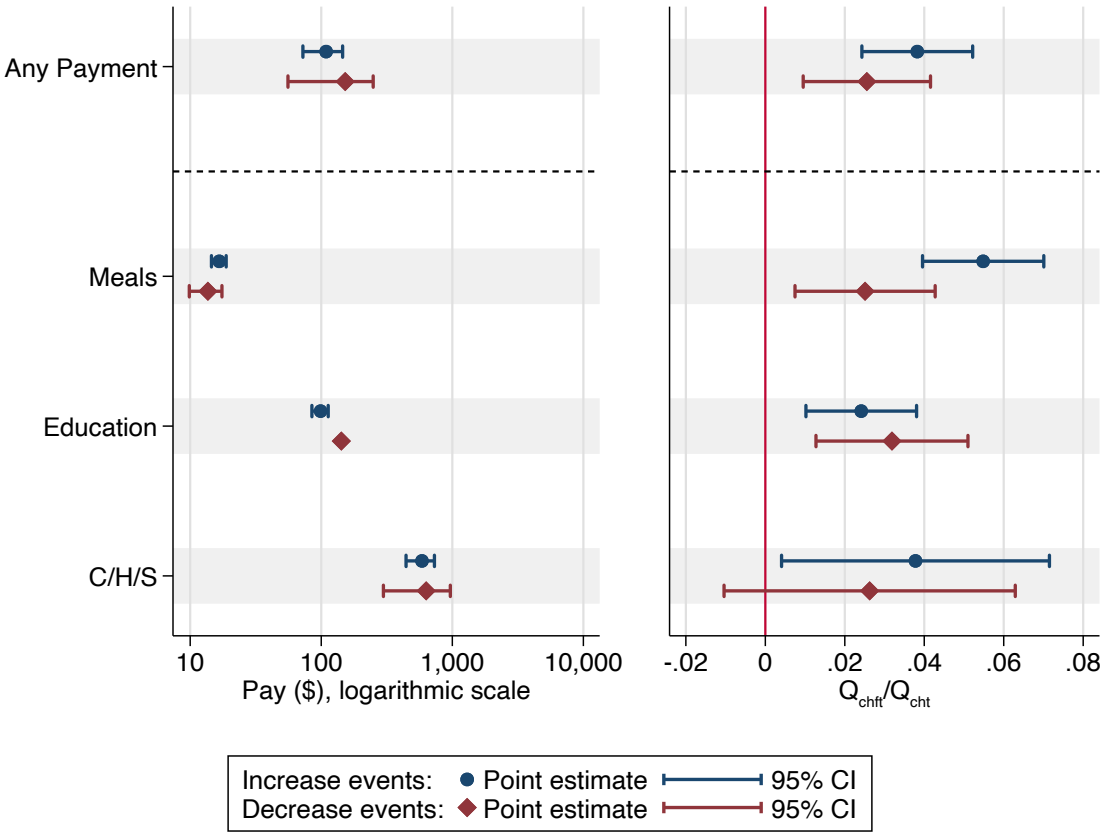
These results shed further light on the variation in payments and sales that underpins the previous TWFE results. While many hospital-firm relationships in our sample were persistent over time, some relationships were instead exposed to discrete shocks in the level of payments, such as the initiation of new payment relationships. These payment shocks involved stronger associations with contemporaneous changes in sales. Moreover, we observe a nearly symmetrical change in post-event procurement, with opposite signs, in increasing and decreasing payment events. This suggests that the relationship between payments and procurement is not persistent, falling once payments stop as quickly as it rose when they began.

Taken together, the above results present a detailed study of how and when payments and medical device procurement outcomes co-move. The event studies suggest that the TWFE model with hospital-firm fixed effects estimated on the full sample likely underestimates the relationship between payment "shocks" and contemporaneous shifts in device procurement. However, the fact that the event study estimates are still smaller than those in the TWFE models with only hospital fixed effects also suggests that there are substantial persistent differences in hospital preferences over specific firms that need to be accounted for. Further, the relationship between payments and procurement seems to be mostly driven by meal payments and the interactions they proxy for, and is manifested in shifting market shares rather than higher prices or total volumes of category-level purchasing.

4 Role of Expertise

In this Section, we attempt to shed some light on the extent to which the differences in market shares associated with differences in payments are in any sense optimal. Recalling the simple model in Section 2.4, the presence of decision errors in device utilization (which could come from a range of choice or information frictions) implies that any true causal effect of payments

Figure 3: Event Study: Effect on Payments and Market Share, by Event Type



Notes: Authors' calculations using Open Payments and Supply Guide data. The figure depicts SDID effect size for increase and decrease payments events, where events are defined by different payment types. Each marker corresponds to a single SDID estimation. The x-axes denotes the SDID effect size for both increase (round markers) and decrease (diamond markers) payment events, where an event is defined based on a speific type of payment (any payment, meals, education, or C/H/S.)

could be welfare improving (if payments correct physician decision errors) or welfare reducing (if payments reinforce or overshoot decision errors). We approach this question by analyzing the deviations of hospitals' purchasing patterns from those of a presumed "expert." In the context of our simple model, if we assume the expert makes no decision errors, then payments and their associated interactions cannot have any informative/corrective role for the expert. However, payments may influence an expert to use more of a device, though potentially to a different extent than a non-expert. Thus, unpaid experts will represent an optimal device mix benchmark to which we compare paid experts as well as paid and unpaid non-experts.

For our experts, we consider teaching hospitals affiliated with the top 75 medical schools (i.e., AMCs) in the U.S., according to the U.S. News & World Report in 2014. Top AMC affiliation is a marker of expertise for two reasons. First, AMCs are widely regarded as being at the frontier of health care research, education, and innovation. Second, treatment at AMCs has long been associated with improved outcomes for medical and surgical care (Keeler et al., 1992; Donald H. Taylor et al., 1992; Burke et al., 2017, 2018), and there is at least suggestive evidence that the mortality differences between teaching and non-teaching hospitals are causal (Geweke et al., 2003; Hull, 2020). While physicians practicing at top AMCs are surely not free from decision errors as in the strictest interpretation of our simple model in Section 2.4, this approach is nevertheless consistent with a range of studies that consider using the preferences of "more expert" or "more informed" consumers as a benchmark (Bronnenberg et al., 2015; Handel and Schwartzstein, 2018). Lastly, it bears mentioning that this approach allows for payments to be welfare-improving in general, but the strictest interpretation assumes that payments cannot be welfare-improving for experts. This assumption is consistent with many AMC hospitals' own perspectives, as revealed by their common practice of banning or sharply restricting pharmaceutical and device company gifts, speaking/travel opportunities, etc. (Association of American Medical Colleges, 2010).

One might be concerned that any differences in device mix between top AMC hospitals and other hospitals are driven by other welfare-relevant preference dimensions. For example,

larger teaching hospitals may attract a different patient population (Shepard, 2021) and those patients may require a different device mix. We argue that, conditional on sufficient controls for hospital characteristics (in particular patient complexity), for the set of fairly routine cardiovascular and orthopedic procedures we study, it is plausible that the medical device needs of patients at top AMC hospitals do not systematically differ from those at other hospitals, or with payment status at any hospital.

As can be seen in Panel (a) of Table 3, hospitals affiliated with top AMCs are different from other hospitals across multiple dimensions. Top AMC hospitals are larger than other hospitals in terms of number of beds and number of affiliated physicians relevant for each device category. Top AMC hospitals' affiliated physicians provide fewer services per period (measured in total Medicare beneficiary-days of service), but also provide higher service intensity (measured in RVUs). RVUs incorporate regulators' estimates of the intensity and effort associated with different procedures (Chan and Dickstein, 2019), and are thus our best proxy for differences in patient mix across facilities. Relative to other hospitals, top AMC hospitals also have a lower share of Medicare patients, but a higher share of Medicaid patients; and are less likely to be nonprofit and likelier to be government owned. Finally, while all top AMC affiliated hospitals are by definition teaching hospitals, only 46 percent of other hospitals are teaching hospitals.

While top AMC hospitals have similar medical device spending per relevant physician, their greater number of affiliated physicians implies that the average top AMC hospital represents a substantially larger device "market" than other hospitals. Correspondingly, their affiliated physicians received more money in payments from medical device firms. Across all firms, the average physician in a top AMC hospital received, on average, $1,270 per-device category per-period, nearly three times the average amount received by physicians in other hospitals.

To understand how payments correlate with usage patterns, we further split the sample by the level of payments the hospitals received. For the sake of simplicity, we split hospital-

periods into low or zero payments ($Pay_{cht} < median(Pay_{cht}|Pay_{cht} > 0)$) vs. high payments ($Pay_{cht} \geq median(Pay_{cht}|Pay_{cht} > 0)$). Within each hospital type (top AMC vs. other), "High Pay" hospitals were larger, affiliated with more relevant physicians, and had higher average service intensity (RVUs).

We modify our regression specification in equation (1) to measure the distance of each vector of medical device firm market shares from the "optimal" benchmark, as follows:[21]

$$\begin{aligned} Q_{chft}/Q_{cht} = \; & \delta_1^e 1[Pay_{chft} > 0] + \delta_2^e 1[Pay_{chft} > 0] * 1[NonTopAMC_h] \\ & + \delta_1^i \log(Pay_{chft}) + \delta_2^i \log(Pay_{chft}) * 1[NonTopAMC_h] \\ & + \gamma_1^e 1[Pay_{cht,\text{-}f} > 0] + \gamma_2^e 1[Pay_{cht,\text{-}f} > 0] * 1[NonTopAMC_h] \\ & + \gamma_1^i \log(Pay_{cht,\text{-}f}) + \gamma_2^i \log(Pay_{cht,\text{-}f}) * 1[NonTopAMC_h] \\ & + X_{chft} * \beta + \theta_{cft} + \eta_{cf} * 1[NonTopAMC_h] + \epsilon_{chft}. \end{aligned} \tag{2}$$

Specified in this way, the vector $\theta_{ct} = \{\theta_{c1t}, \theta_{c2t}, \theta_{c3t}, \theta_{c4t}\}$ captures the "optimal" mix of medical device purchases from each of the top four firms in the device category (the "unpaid expert" benchmark) in each period, while the vector $\eta_c = \{\eta_{c1}, \eta_{c2}, \eta_{c3}, \eta_{c4}\}$ captures the average deviation from the optimal mix among non-Top AMC hospitals, *ceteris paribus*. To the extent that non-Top AMC hospitals respond differently to payments than Top AMC hospitals, the differences between $(\delta_1^e, \delta_1^i, \gamma_1^e, \gamma_1^i)$ and $(\delta_2^e, \delta_2^i, \gamma_2^e, \gamma_2^i)$ would capture that difference in response. We note that this specification focuses on differences across hospitals based on their time-invariant characteristics (Top AMC status), and therefore inherently does not identify the association between payments and utilization as tightly as the TWFE or event study specifications in Section 3, which control for each hospital's persistent preferences over each firm. We instead focus on controlling as richly as possible for observable hospital characteristics that might predict differences in patient population.

Apart from estimating equation (2) with our standard weighting scheme,[22] we used two

[21] For tractability, we restrict our analysis to the top four medical device firms, as measured by total sales, in each device category.

[22] Weighting each of the eight focal device categories equally so that each of the statistics below should

additional approaches to account for potential differences in device mix usage across hospitals with different patient populations. In the first approach, we first performed a probit regression of $1[TopAMC_h]$ on log number of relevant physicians, physician work RVU, log physician beneficiary-days, % Medicare, % Medicaid, log hospital beds, and hospital indicators for nonprofit, government, and teaching status, with category-varying coefficients. We then weighted observations in the estimation of equation (2) using inverse probability weights (IPWs) resulting from this regression.[23] IPW-weighted summary statistics for each hospital type are presented in Appendix Table A12; when we apply these weights, our regression sample displays much smaller differences between Top AMC hospitals and other hospitals along observable dimensions.

In the second alternative approach, we explicitly focused on the average intensity of services provided by relevant physicians as our proxy for the patient mix. We constructed a matched sample of hospitals based on the average physician work RVU. Namely, for each top AMC hospital with low/zero pay, we find the closest hospital in that period (in terms of average physician work RVU) in each of the three other hospital groups we've defined. Each match identified four hospitals, one from each expertise/payment groups, that had the closest average physician work RVU in that given period. We then estimated equation (2) while controlling for match group fixed effects. Appendix Table A13 presents the results of estimating three versions of equation (2): unweighted, IPW-weighted, and matched sample.

Panel (b) of Table 3 summarizes the estimates of equation (2) by calculating an average "Distance from Benchmark" metric for each of our four expertise/payment groups. A hospital's Distance from Benchmark within a given device category is the Euclidean distance of the vector of market shares predicted by equation (2), from the optimal mix of device purchases predicted by our estimates of θ_{cft}, given each hospital's observable characteristics and payments. Each row of panel (b) shows the summary "Distance from Benchmark" results

be interpreted as applying *within the average focal device category.*

[23]The distributions of the resulting propensity scores are presented in A2. We note that Top AMC and non-Top AMC hospitals distributions overlap. We further note that nearly 58% of hospitals in the non-Top AMC hospital distributions have a propensity score close or equal to zero.

for one of the three approaches described above—unweighted, IPW-weighted, and matched sample. The results are nearly identical when we up-weight hospitals that are more like top AMCs along observable dimensions, such as size, patient volume, and care intensity. Thus, for the sake of brevity, we focus on the IPW-weighted results in the below discussion.

We find that, on average, hospitals receiving payments were further away from the device choices made by our benchmark unpaid experts. Among Top AMC affiliates, hospitals that received above median pay were 2.1 times further away from the benchmark than low/zero pay Top AMC hospitals. Among non-Top AMC hospitals, high pay hospitals were 4 times further away from the benchmark than low/zero pay non-Top AMC hospitals. As can be seen in Appendix Table A13, the coefficients on the intensive and extensive margin payment variables are similar for Top AMC and non-Top AMC hospitals, so the larger distance for high pay Top AMC affiliates in panel (b) is driven by the higher payments observed at hospitals in that category.

To summarize, we find that Top AMC hospitals purchase a different mix of medical devices than other hospitals, even when controlling for hospital characteristics that may influence purchasing decisions, like patient mix, ownership, and size. Hospitals that receive more physician payments change the mix of devices they purchase in a way that distances them further from the estimated mix used by Top AMC hospitals with zero physician payments. If the supposition that Top AMC hospitals have the clinical expertise to make optimal device choices in the absence of payments from industry is correct, then our results imply that payments are associated with use of a suboptimal mix of medical devices. This association could be driven by payments causally pushing non-experts' use of medical devices further from the optimal mix, or by firms targeting payments to hospitals that would make less optimal device choices even in the absence of payments.

Table 3: Association between Market Share, Top AMC Status, and Payments

(a) Summary Statistics

	Top AMCs			Other Hospitals		
	All	Low/Zero Pay	High Pay	All	Low/Zero Pay	High Pay
Hospital count	88	67	67	640	583	392
Hospital-period count	518	244	274	3,669	2,529	1,140
Observations	2,013	947	1,066	14,277	9,870	4,408
Pay_{cht} ($1,000s)	1.55	0.01	2.74	0.54	0.01	1.69
	(6.98)	(0.03)	(9.15)	(7.67)	(0.03)	(13.58)
$Sales_{cht}$ ($1,000s)	48	40	54	43	41	49
	(84)	(81)	(86)	(95)	(95)	(94)
Num. of relevant physicians	15	10	19	8	7	11
	(13)	(10)	(15)	(8)	(6)	(9)
Physician work RVU	1.79	1.63	1.92	1.50	1.47	1.58
	(0.99)	(1.04)	(0.92)	(1.34)	(1.44)	(1.06)
Physician beneficiary-days	1,169	1,258	1,082	2,003	1,991	2,022
	(1,022)	(1,158)	(833)	(1,464)	(1,454)	(1,478)
% Medicare	39	40	38	47	47	46
	(10)	(11)	(8)	(9)	(9)	(9)
% Medicaid	27	27	26	21	21	20
	(13)	(15)	(10)	(10)	(10)	(9)
Beds	577	490	653	304	276	363
	(390)	(401)	(361)	(206)	(187)	(230)
Nonprofit (%)	63	63	63	85	84	86
Government (%)	32	32	33	9	9	8
Teaching (%)	100	100	100	46	42	55

(b) Distance from Benchmark (Top AMCs, No Payments)

	Top AMCs			Other Hospitals		
Distance from benchmark	All	Low/Zero Pay	High Pay	All	Low/Zero Pay	High Pay
Unweighted	0.016**	0.011**	0.022**	0.029**	0.024**	0.039**
	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)
IPW-weighted	0.016**	0.010**	0.028**	0.040**	0.036**	0.050**
	(0.004)	(0.003)	(0.006)	(0.011)	(0.010)	(0.012)
Matched hospitals	0.017**	0.011**	0.023**	0.043**	0.039**	0.046**
	(0.004)	(0.003)	(0.006)	(0.007)	(0.007)	(0.008)

Notes: Panel (a): Key hospital and hospital-category statistics by expertise/payment group, as defined in Section 4. All statistics are averaged across device categories, weighting each category equally. Device payments and purchasing statistics are from authors' calculations using Open Payments and Supply Guide data, respectively. Panel (b): Average distance from benchmark (Top AMCs with no payments) for each expertise/payment group, derived from estimating equation (2) using three alternative weighting approaches. Standard errors calculated using the delta method in parentheses. ** p<0.01, * p<0.05.

5 Discussion and Conclusion

A growing body of research has explored the potential for inefficiency in procurement driven by factors such as (lack of) information or expertise, agency, and supplier firms' efforts to exploit information and agency frictions. The typical study has looked at how procurement outcomes change with changes in the rules governing players' behavior. We take a different approach, exploring the relationship between multiple facets of procurement outcomes and direct data on supplier firms' interactions with buyer agents. The key input to our paper is a novel merger of two administrative data sets on eight major implantable medical device categories across a large sample of US hospitals. This allows us to present several new facts regarding industry payments to physicians and hospital procurement outcomes for the promoted medical devices.

First, we find that payments are ubiquitous, with nearly all US hospitals having affiliated physicians who received some payment related to the devices they use. Second, payments are strongly associated with device procurement outcomes within category-hospital and category-hospital-firm. These associations exist on the extensive and intensive margins and are similar across a range of device categories. Third, procurement outcomes are mostly correlated with meal payments, rather than education or consulting/speaking payments. This finding has two potential interpretations. On the one hand, the value of meal payments is very low compared to physicians' incomes, suggesting that payments do not function as "bribes" as commonly defined (i.e., they do not offer much pecuniary benefit to the physician). On the other hand, the low correlation between payments related to education and procurement outcomes suggests that, if payments do impact procurement, it may not be through providing physicians with information, at least not through this more formal educational channel.

Finally, there is little evidence that payments are associated with the types of procurement waste typically highlighted in the economic literature and popular press: an increase in the total number of devices procured (from any seller), or an increase in the price per unit

procured. Despite this, we still find that payments are associated with "worse" procurement outcomes, defined as a suboptimal mix of medical devices relative to the usage patterns of "expert" physicians practicing at top AMCs.

These results suggest that payments from device firms to physicians are an important element of medical technology markets that deserve further study. In particular, any normative evaluation of physician-industry relations will need to understand how payments affect welfare in the face of other market frictions that may distort physician choice. Given our finding that payments are associated with business stealing rather than market expansion, the impact of payments on patient health outcomes will depend crucially on the extent of vertical and horizontal quality differentiation in device markets, a subject on which there is unfortunately limited evidence.[24] Finally, the nature of device firm-physician relationships introduce additional factors to consider, which are not present to the same extent in the pharmaceutical industry: the actual treatment effects of device sales representatives as partners in care delivery in the operating room, and the potential impacts of these relationships on device research and development.

An important limitation of our study is that our analysis is focused on device categories that are technologically "mature".[25] While new products have been developed and marketed in each of these categories during the analysis period, they generally retained the same clinical indications and required the same surgical techniques as already existing products in the category. In contrast, technologically novel devices (and device categories) may require the physician to learn a new surgical technique, change their workflow in the operating room, or make other substantial changes to their knowledge base or practice patterns before they can adopt the use of the device.[26] Such a process likely necessitates significant interactions

[24]Many medical devices, including many of the high-tech implantable devices of the kind studied in this paper, are approved via the FDA's accelerated 510(k) pathway, which does not require evidence from clinical trials, and there is significant uncertainty about product quality even after clinical trials and after products are on the market (Grennan and Town, 2020; Stern, 2017).

[25]The newest device category in our analysis is drug-eluting stents. The FDA granted its first DES device approval in 2002.

[26]For example, see Leon et al. (2014) for a discussion of the challenges involved with adoption of Transcatheter Aortic Valve Replacement.

between physicians and device manufacturers, which could result in high-valued payments to the physician for education, travel, and meals. Future research on the impact of such interactions on the adoption of new medical technology would be highly valuable.

A Data Appendix

A.1 Matching payments and Medicare data

We match physicians in the Open Payments data to national provider identifiers using name, address, and specialty. Beginning with the most stringent match requirement (matching on full name, exact street address, and exact first specialty), we iteratively relax the requirement for a successful match. Table A1 below shows the match criteria employed, in decreasing order of stringency, and rates of successful matching. Using this procedure, we are able to match 728,017 of the 744,733 physicians appearing in the 2014-2017 OP data to NPIs in the Medicare data.

A.2 Matching payments and Supply Guide data

In order to analyze utilization data for products documented in the OP data as being promoted to physicians during 2014-2017, we match the OP data to the firms and product categories in the Supply Guide data.

First, we limit the scope of our analysis to device-related payments. Where appropriate, we classify firms in the database as being drug-only or device-only firms. Firms for which 95 percent of product-linked payments are associated with drugs are classified as drug firms, and vice versa for device firms. For the relatively small subset of firms making payments promoting both drugs and devices, we then classify payments by firm and specialty of receiving physician. For example, we consider a firm to be a "device firm" in a specific specialty if 95 percent of product-linked payments made to physicians in that specialty are associated with devices.[27] Using this procedure, we are able to classify 99 percent of all individual payments, comprising 97.3 percent of payments by total dollar amount, as being either drug- or device-related.[28]

[27]For example, 97 percent of product-linked payments made by Allergan to plastic and reconstructive surgeons are device-related.

[28]For comparison, directly using each payment's product description will only classify 82 percent of all

Table A1: Open Payments Physician-NPI Match Criteria

Step	Matching Criterion	Matches	Cum. Pct.
1	Surname, M.I., first name, full practice address, cred., 1st spec.	94,920	12.33
2	Surname, M.I., first name, full practice address, cred., 2nd spec.	5,899	13.10
3	Surname, M.I., first name, full practice address	4,830	13.73
4	Surname, M.I., first name, full business address	59,035	21.40
5	Surname, first name, full practice address, cred., 1st spec.	36,564	26.15
6	Surname, first name, full practice address, cred., 2nd spec.	2,598	26.49
7	Surname, first name, full practice address	3,805	26.98
8	Surname, first name, full business address	26,147	30.38
9	Surname, M.I., first name, practice add. state, 9-digit zipcode, cred., 1st spec.	119,794	45.95
10	Surname, M.I., first name, practice add. state, 9-digit zipcode, cred., 2nd spec.	8,188	47.01
11	Surname, M.I., first name, practice add. state, 9-digit zipcode	8,616	48.13
12	Surname, M.I., first name, business add. state, 9-digit zipcode	67,521	56.90
13	Surname, first name, practice add. state, 9-digit zipcode, cred., 1st spec.	59,174	64.59
14	Surname, first name, practice add. state, 9-digit zipcode, cred., 2nd spec.	4,520	65.18
15	Surname, first name, practice add. state, 9-digit zipcode	9,536	66.42
16	Surname, first name, business add. state, 9-digit zipcode	39,933	71.61
17	Surname, M.I., first name, practice add. city, state, 5-digit zipcode, cred., 1st spec.	61,348	79.58
18	Surname, M.I., first name, practice add. city, state, 5-digit zipcode, cred., 2nd spec.	3,442	80.03
19	Surname, M.I., first name, practice add. city, state, 5-digit zipcode	6,604	80.88
20	Surname, M.I., first name, business add. city, state, 5-digit zipcode	28,294	84.56
21	Surname, first name, practice add. city, state, 5-digit zipcode, cred., 1st spec.	32,218	88.75
22	Surname, first name, practice add. city, state, 5-digit zipcode, cred., 2nd spec.	2,277	89.04
23	Surname, first name, practice add. city, state, 5-digit zipcode	7,322	89.99
24	Surname, first name, business add. city, state, 5-digit zipcode	18,127	92.35
25	Surname, M.I., first name, practice add. city, state, cred., 1st spec.	3,736	92.84
26	Surname, M.I., first name, practice add. city, state, cred., 2nd spec.	340	92.88
27	Surname, M.I., first name, practice add. city, state	787	92.98
28	Surname, M.I., first name, business add. city, state	911	93.10
29	Surname, first name, practice add. city, state, cred., 1st spec.	2,658	93.45
30	Surname, first name, practice add. city, state, cred., 2nd spec.	241	93.48
31	Surname, first name, practice add. city, state	944	93.60
32	Surname, first name, business add. city, state	715	93.69
33	Surname, M.I., first name, practice add. state, 3-digit zipcode,cred., 1st spec.	2,717	94.05
34	Surname, M.I., first name, practice add. state, 3-digit zipcode,cred., 2nd spec.	224	94.07
35	Surname, M.I., first name, practice add. state, 3-digit zipcode,	577	94.15
36	Surname, M.I., first name, business add. state, 3-digit zipcode,	748	94.25
37	Surname, M.I., first name, practice add. state, cred., 1st spec.	5,125	94.91
38	Surname, M.I., first name, practice add. state, cred., 2nd spec.	452	94.97
39	Surname, M.I., first name, practice add. state	1,242	95.13
40	Surname, M.I., first name, business add. state	346	95.18
41	Surname, M.I., first name, cred., 1st spec.	6,176	95.98
42	Surname, M.I., first name, cred., 2nd spec.	645	96.06
43	Surname, first name, cred., 1st spec.	10,508	97.43
44	Surname, first name, cred., 2nd spec.	996	97.56
45	Surname, M.I., first name	2,067	97.83
Unmatched		16,716	2.17

Notes: The 45 sequential steps used to match physicians in the Open Payments data set to NPPES NPIs based on name, address, credentials and medical specialty. Each row represents the step criteria for matching physician NPIs to OP physicians, and the number of additional matches identified in that step, and the share of Open Payments physicians identified by that step.

Next, we attribute each device-related payment in the OP data to a firm and UMDNS code in the Supply Guide data. In the Supply Guide data, the UMDNS system is employed to classify any device or supply based on its intended purpose, with some distinctions for mechanism of action. It covers all medical devices and supplies, clinical laboratory equipment and reagents, and selected hospital furniture, among other items. For example, drug-eluting coronary stents have UMDNS code 20383. In the OP data, by regulation, drug and device firms must report the specific drug or device associated with any physician payment meeting the reporting threshold. While drugs are identified by unique (and very specific) national drug codes, devices are only identified by free-form text fields. These fields are filled by the firm submitting the payment information, and vary significantly in specificity and accuracy across firms and over time. Some entries in this field describe a range of products rather than a single brand, or refer to the whole range of devices produced by the firm. To avoid confusion, we refer to an entry in the OP free-form text field as an *object name* (as opposed to a device name), describing an *object* (as opposed to a device).[29] Approximately 95 percent of device-related payments made between 2014-2017 are associated with objects, amounting to $2.8 billion, or 84 percent of the total value of device-related payments.

Our matching methodology is summarized (in order) in Table A2. Manually identifying the UMDNS code of each object is infeasible, as there are over 15,000 unique objects in the OP data. Instead, we manually identify UMDNS codes for the top-paid objects (objects associated with payments totaling $1 million or more over 2014-2017), and algorithmically identify other objects. Steps 1-4 and 7 involve manual inspection. Steps 5-6 and 8 involve the algorithmic match of the remaining objects.

The breakdown of manual matching of the 485 objects associated with payments totaling $1 million or more over 2014-2017 is shown in Table A3 below.[30]

individual payments, or 83 percent of total payment dollars.

[29]Firms can report up to five objects for each unique payment. If a payment is associated with more than one object, we divide the payment amount evenly across the associated objects and count each object association as a separate payment.

[30]Of the 451 Open Payments objects associated with a total of $1 million in payments or more, we were unable to match 40 objects to Supply Guide.

Table A2: Identifying Payments' UMDNS Codes

Step	Procedure	Objs. IDed (Cum.)	Payment Count		Total Payment Value ($mil)	
			Count	Cum. Share (percent)	Amount	Cum. Share (percent)
1	Manually identify device brands for all {named product,firm} pairs with at least $1mil in total payments over 2014-2017	236	726,936	16.19	804	24.03
2	Manually identify firm device product lines for all {named product,firm} pairs with at least $1mil in total payments over 2014-2017	275	917,839	20.44	948	28.32
3	Manually identify device categories for all {named product,firm} pairs with at least $1mil in total payments over 2014-2017	404	1,522,316	33.89	1,780	53.18
4	Manually identify device categories for all {named product,firm} pairs with at least $1mil in total payments over 2014-2017	410	1,642,066	36.56	1,890	56.47
5	Identify firm by id; identify device by exactly matching the {named product} field to ECRI device descriptions	2,599	2,277,204	50.70	2,081	62.18
6	Identify firm by id; identify device by matching text in {named product} field to ECRI device descriptions	3,875	2,541,548	56.59	2,167	64.76
7	Identify firm by id; identify device by matching text in {named product} field to any substring of ECRI device descriptions	3,913	2,563,964	57.09	2,172	64.88
8	Identify firm by id; identify device by matching brand-specific text in {named product} field to ECRI device descriptions, where text in {named product} has been stripped from all generic terms	5,492	2,699,617	60.11	2,205	65.89
9	Identify device category by category-specific words in {named product}	5,828	2,751,652	61.27	2,245	67.08
10	Calculate device payment UMDNS mix for each firm-speciaty pair, apply mix to unidentified objects with firm-specialty payments	5,843	2,927,414	65.18	2,786	83.23
11	Identify device category for all firm payments by ECRI sales by UMDNS	6,355	2,973,387	66.20	2,812	84.01
	Unidentified	8,907	1,518,005	33.80	535	15.99

Notes: Authors' calculations using Open Payments and CMS Part-B Utilization data. Total payment value is calculated over all device-related payments associated with objects in 2014-2017.

Table A3: Categorizing Top Paid Objects

Object Type	Num. of Objs.	Payment Value ($mil)
Single device brand	242	822.89
Product line portfolio	42	151.60
Device category	134	851.64
Firm OP portfolio	19	161.49
Firm sales portfolio	7	111.71
Other objects	41	85.47

Notes: Authors' calculations using Open Payments data. Distribution of Open Payments object types, for all device-related objects with a payment value totaling $1 million or more over over 2014-2017.

A taxonomy of object specificity arose from this exercise: device brands, device product lines, device categories, firm OP portfolio, and complete firm portfolio. Here, we provide some examples of how this matching would work in practice, referring to real objects appearing in the OP data for which we can find public records in FDA's public Global Unique Device Identification Database (GUDID).[31] Our Supply Guide data use agreement prohibits us from disclosing specifics on transactions associated with any particular firm or brand.

- **Single device brands** in the OP data refer to branded medical devices and device systems (for example, the Medtronic-paid object "cd horizon" refers to Medtronic's CD Horizon^{TM} spinal system). We match such objects to all related transactions in the Supply Guide data using the Supply Guide item descriptions. A single device brand is often associated with several distinct UMDNS codes. In these cases, given that a payment-related interaction would be simultaneously promoting an indivisible product (or system), each associated UMDNS code receives a *payment weight* of 1. That is, for a $1 payment for a given brand, *each* of the brand's UMDNS codes has $1 in payments from the brand's firm attributed to it. We also manually confirm that (a) the string match captures all items related to the brand; and (b) that no other items are linked to the object.

- **Product line portfolios** identify a range of brands under a specific firm, often a product line. For example, Medtronic's "CVI" object refers to its line of chronic venous insufficency products, including VenaSeal^{TM} and ClosureFast^{TM}; and Boston Scientific's "pain management" object refers to the brands and product descriptions listed on Boston Scientific's "Pain Medicine Products" website (e.g., "neurostimulator," "spinal cord stimulator (SCS)," Spectra^{TM}, CoverEdge^{TM}, Montage^{TM}, and Precision^{TM}). We match such objects to all brands (e.g. Spectra^{TM}), and product descriptions (e.g., "spinal cord stimulator") under the relevant product line portfolio, then manually match the brands and product descriptions to item descriptions in the Supply Guide data.

[31] GUDID is available online at https://AccessGUDID.nlm.nih.gov.

Lastly, we apportion the dollar value of a product line portfolio-related object payment across matched UMDNS codes according to each UMDNS code's sales share for that firm, within the relevant product line transactions in Supply Guide.

- **Device categories** identify general categories of devices. We match these objects to their appropriate UMDNS codes directly, rather than through transaction-level data on specific brands. For example, we associate payments towards an object named "hips" with all hip-related UMNDS codes in our data set.[32] We apportion the dollar value of a given firm's "hips" payments across UMDNS codes in proportion to that firm's sales in each hip-related UMDNS code.

- **Complete firm portfolios** are objects that: (a) describe the entire sales portfolios of their firms; and (b) are the only objects the firms make payments for. For example, the firm Davol's sole OP object has the name "surgical," and Davol is observed in the GUDID data to *only* sell a range of surgical products. We associate such objects with the entire range of their firms' products observed in Supply Guide, and apportion payment dollar values across UMDNS codes according to the specific firms' sales in each UMDNS code.

After the above four manual matching steps, we use an algorithmic match to identify two types of objects: ones that identify a brand, and ones that identify a device category.

- **Device brands.** In Steps 5-8, we manually match OP firms to Supply Guide firms, then iteratively string-match object names to Supply Guide item descriptions, with each iteration requiring a less stringent match.[33] These algorithmic matches are accepted if an object matches to a unique UMDNS code in the Supply Guide data.

[32]These are: Prostheses Joint Hip Acetabular Component, Prostheses Joint Hip Femoral Component, Prostheses Joint Hip Total, Trial Prostheses Joint Hip, Prostheses Joint Hip, and Prostheses Joint Hip Acetabular Component Shell.

[33]In decreasing order of stringency, we collect the following matches: OP object name matches exactly to Supply Guide item description; OP object name matches exactly to Supply Guide item description sub-string; "cleaned" OP object name matches exactly to Supply Guide item description; and "cleaned" OP object name matches exactly to Supply Guide item description sub-string. When we "clean" an object name, we remove common generic words that do not identify specific brands. We manually reviewed 4,700 words

- **Device categories.** In Step 9, we attempted to identify the device categories of the objects remaining unidentified after steps 1-8. We manually reviewed all 1,071 word-pairs appearing in object names with (a) over $10K in payments in 2014-2017; or (b) appearing in ten or more object names.[34] We then manually flagged word-pairs that represent device categories. We identified 174 such pairs.[35] For illustration, see Appendix Table A4 for terms flagged as associated with the "spine" device category. Finally, for OP objects associated with a set of UMDNS codes via the device category match, we apportion the dollar value of payments across UMDNS codes according to the relevant firm's sales share in each UMDNS code.

After performing steps 1-6, we attribute payments to UMDNS codes via one more "roundup" exercise for nonspecific objects:

- **Firm OP portfolios** identify objects with generic names referring to the entire firm portfolio (e.g., "all," "general therapies," or "product portfolio"). Neither device brand nor device category can be inferred from these objects. Furthermore, these terms may represent different device categories, depending on the recipient; a firm making "product portfolio" payments to both cardiologists and orthopedists is not referring to the same portfolio. We assigned UMDNS codes to these objects based on matches made in previous steps. For each firm and each provider specialty, we use previously-identified objects to calculate the value of payments made by UMDNS code. We then assign these UMDNS codes to the generic object when made to physicians of the same specialty.[36]

appearing in object names which either (a) were associated with over $10K in payments in 2014-2017, or (b) appeared in ten or more named objects. We removed all those representing generic terms, such as "system," "instruments," "medical," and "products."

[34] We exclude generic terms such as "system," "instruments," as well as terms identified as brand names in previous steps.

[35] We restrict our search to word-pairs rather than single terms to avoid overgeneralizing when possible. For example, the term "thoracic" may be associated with either the spine or the aorta, while the pair {"thoracic", "fixation"} can only refer to a device implanted in the spine.

[36] For example, if all previously-identified payments made by a firm to orthopedists are related to knees and hips, we would assume that any "product portfolio" payments made by the firm to orthopedists are only related to knees and hips.

Table A4: Term Pairs Associated with the "Spine" Category

Term 1	Term 2	Frequency	Associated value (in $mil)
Augmentation	Vertebral	1,110	1,391,172
Fusion	Posterior	423	569,395
Reconstruction/fixation	Thoracic	303	30,416
Fixation	Spinal	193	1,584,406
Spine	Truss	98	526,595
Anterior	Fusion	49	24,423
Interbody	Spinal	41	568,367
Fusion	Interbody	40	507,143
Cages	Spinal	28	481,338
Cervical	Posterior	27	296,966
ALIF	Vault	17	845,385
Cervical	Interbody	13	615,080
Cervical	Fixation	13	379,622
ALIF	PLIF	4	519,826
Cage	Lumbar	2	191,682
ALIF	Cages	2	75.496
Invasive	Pedicle	1	67.000
Rods	Spinal	1	57,280

Notes: Authors' calculations using Open Payments data. Term pairs (terms appearing jointly in the same object description) associated with spinal devices.

- **Complete firm portfolio.** In Step 8, after exhausting the information in the object name field in the OP data, we turn to using information in the Supply Guide data set to identify the UMDNS association of device-related payments. We define a firm to be a "single-category firm" if at least 75 percent of its sales are concentrated within one UMDNS category. For nested categories, we assign the highest level category identified. For example, a firm specializing in elbow joint reconstruction will also be identified as specializing in general joint reconstruction and, in turn, in orthopedics. Supposing that the narrowest specialization of the firm is elbow joint reconstruction (i.e., at least 75 percent of the sales made by this firm are in this category), we assign all device-related payments made by this firm to physicians, which were not identified in previous steps, to the elbow joint category.

Ultimately, we associate 6 percent of device-related payments, associated with 84 percent of the total dollar value of device-related general payments to individual physicians, with a firm-UMDNS code pair in the Supply Guide data.

A.3 Focal device categories

After performing the above mapping between OP firm-objects and Supply Guide firm-UMDNS codes, we arrive at a list of 1,721 UMDNS codes with any associated OP payments. We organize these UMDNS codes into 260 categories based on similarities in clinical use. Categories are structured hierarchically, based on hierarchies established in the Supply Guide data, which we manually correct in some cases. Table A5 below summarizes the top 30 categories by total payments 2014-2017, in descending order of total payments. We construct this list by collapsing "small" device sub-categories (sub-categories with less than $5 million in total payments over the 2014-2017 period) into their parent category.

The vast majority are under the top category grouping of "Heart and Vascular" or "Orthopedics," though the single largest category is "Robotic Arms Sterile Supplies."

Table A5: Top Device Categories in Open Payments

Device Category	Payments excl. Royalties and Ownership			Payments incl. Royalties and Ownership		
	Total Payment Value, 2014-2017 ($mil)	Share of IDed Devices Payments (percent)	Share of All Device Payments (percent)	Total Payment Value, 2014-2017 ($mil)	Share of IDed Devices Payments (percent)	Share of All Device Payments (percent)
Robotic Arms Sterile Supplies	97.23	7.85	6.86	97.23	3.62	3.42
Orthopedics, Joints, Knee and Hip, *Knees*	**82.67**	**6.68**	**5.83**	**297.39**	**11.08**	**10.46**
Orthopedics, Spine, *Screws*	**64.52**	**5.21**	**4.55**	**305.50**	**11.38**	**10.75**
Orthopedics, Joints, Knee and Hip, *Hips*	**52.11**	**4.21**	**3.67**	**187.75**	**7.00**	**6.61**
Orthopedics, Spine, *Spacers*	**47.06**	**3.80**	**3.32**	**163.94**	**6.11**	**5.77**
Heart and Vascular, Cardiac, Valves, Transcatheter, TAVR	42.11	3.40	2.97	63.62	2.37	2.24
Heart and Vascular, Cardiac, Rhythm, ICD	37.08	2.99	2.62	45.13	1.68	1.59
Pain Mgmt, Spinal Cord, SCS	36.95	2.98	2.61	41.16	1.53	1.45
Heart and Vascular, Vascular, Stents, Coronary, Balloon-Expandable, Drug-Eluting *DES*	**34.20**	**2.76**	**2.41**	**36.18**	**1.35**	**1.27**
Heart and Vascular, Vascular, Stents, Stent/Grafts, *AAA*	**31.79**	**2.57**	**2.24**	**54.12**	**2.02**	**1.90**
Orthopedics, Joints, Suture Anchors	30.67	2.48	2.16	122.14	4.55	4.30
Orthopedics, Joints, Extremities, Shoulder and Elbow, *Shoulders*	**28.41**	**2.29**	**2.00**	**86.46**	**3.22**	**3.04**
Heart and Vascular, Vascular, Catheters, Angioplasty, *Atherectomy*	**27.85**	**2.25**	**1.96**	**37.32**	**1.39**	**1.31**
Procedure Kit/Trays	24.45	1.97	1.72	32.88	1.23	1.16
Mesh Collagen	20.81	1.68	1.47	21.91	0.82	0.77
Heart and Vascular, Cardiac, Catheters, Mapping/Ablation, Ablation	19.45	1.57	1.37	23.73	0.88	0.83
Orthopedics, Fixation, Screws	17.28	1.40	1.22	67.30	2.51	2.37
Optics, Intraocular, General, Lenses Intraocular	15.10	1.22	1.07	17.51	0.65	0.62
Heart and Vascular, Cardiac, VAD	14.95	1.21	1.05	15.33	0.57	0.54
Heart and Vascular, Cardiac, Rhythm, Pacemakers, General, Pacemakers Cardiac Implantable	12.78	1.03	0.90	15.43	0.57	0.54
Mesh Polymeric	11.95	0.97	0.84	13.70	0.51	0.48
Heart and Vascular, Vascular, Stents, Intracranial Artery, Flow Diversion	11.04	0.89	0.78	41.29	1.54	1.45
Microspheres Embolization	10.72	0.87	0.76	10.73	0.40	0.38
Penile Prostheses	10.40	0.84	0.73	12.02	0.45	0.42
Orthopedics, Fixation, Bolts, Bolts Bone	9.29	0.75	0.66	13.20	0.49	0.46
Heart and Vascular, Vascular, Catheters, Angioplasty, Balloon	9.28	0.75	0.65	11.56	0.43	0.41
Heart and Vascular, Cardiac, Valves, General, Prostheses Cardiac Valve Biological	8.44	0.68	0.60	17.84	0.66	0.63
Heart and Vascular, Vascular, Stents, Peripheral	8.30	0.67	0.59	9.81	0.37	0.35
Orthopedics, Spine, Rod Implants, General, Orthopedic Rod Implants Spinal	8.12	0.66	0.57	26.42	0.98	0.93
Heart and Vascular, Vascular, Catheters, Guiding, General, Catheters Vascular Guiding	8.09	0.65	0.57	10.84	0.40	0.38
Top 30 device categories	833.11	67.27	58.76	1,899.41	70.77	66.83

Notes: Authors' calculations using Open Payments data. The top 30 device categories in terms of total payment value (excl. royalty and ownership payments) over 2014-2017. These categories represent 67.27 percent of the total payment value of payments for which we are able to identify the device, or 58.75 percent of all device-related payments over the same period.

In order to focus our analysis on a manageable number of important product categories, we begin by focusing on 13 product categories linked to OP payments of over $25 million during 2014-2017.

From these, we further exclude orthopedic suture anchors and orthopedic (non-spinal) screws. Unlike the other device categories we study, suture anchors and orthopedic screws can be used in a broad class of orthopedic surgeries involving a range of body parts, such as ankles, knees, hips, shoulders, and thumbs. We also exclude Robotic Surgery supplies, TAVR, SCS, and ICD; the former refers to the Da Vinci robotic surgery system marketed by Intuitive Surgical, the latter to the transcatheter valve replacement product marketed first by Edwards and subsequently by Medtronic. Robotic surgery systems are different from our other device categories in that they compete with traditional open and laparascopic surgery alternatives (and their associated devices) across many types of surgeries (e.g., cornea surgery, prostatectomy, nephrectomy, and hysterectomy procedures, to name a few). TAVR is a much less mature category than the other "top" categories, having received its first FDA approval in 2011. Finally, PriceGuide did not include sales data for two prominent firms operating in the SCS and ICD markets (one in each), leaving us unable to fully observe hospital procurement in these categories. For this reason, we exclude the four categories from our main analysis and limit our focus to the remaining eight "important" device categories. These are bolded in Table A5, noting our preferred abbreviation for each category in italics. They account for 41 percent of the dollar value of device-related general payments that were matched to the Supply Guide data.

Our final set of included categories are **AAA** stent grafts, **atherectomy** catheters, **DES** coronary stents, **knees**, **hips**, **shoulders**, spinal **screws**, and spinal **spacers**.

We define "relevant" physicians for each product category as those who may perform the procedure in which the device is implanted based on their specialty. To do this, we manually match device UMDNS codes to HCPCS (Healthcare Common Procedure Coding System) procedure codes using device firms' clinician billing guides. We then used the Medicare data

to identify the specialties mostly commonly billing under each UMDNS' HCPCS codes. We consider a specialty to be relevant to a specific procedure if physicians in that specialty account for 10 percent or more of all Medicare billing for it. The specialties relevant to each device category are: Vascular Surgery for AAA; Cardiology (including Interventional Cardiology) and Vascular Surgery for Atherectomy; Cardiology (including Interventional Cardiology) for DES; Orthopedic Surgery for Hips, Knees, and Shoulders; and Orthopedic Surgery and Neurosurgery for Screws and Spacers.

B Appendix Tables and Figures

Table A6: Sample Hospitals

	Open Payments		Supply Guide		
	Full Sample	Focal Categories	Full Sample	Focal Categories	Analytic Sample
Hospital beds	170.62	215.84	242.06	262.66	274.45
	(199.72)	(215.76)	(231.63)	(233.13)	(237.32)
Percent Medicare	50.04	48.40	47.52	46.44	46.73
	(13.84)	(11.99)	(12.65)	(11.79)	(10.43)
Percent Medicaid	18.31	19.50	20.77	21.32	21.07
	(10.84)	(10.69)	(11.35)	(11.19)	(10.25)
Non-Profit	0.62	0.65	0.81	0.82	0.81
	(0.49)	(0.48)	(0.39)	(0.39)	(0.39)
Government	0.21	0.15	0.12	0.11	0.11
	(0.41)	(0.36)	(0.33)	(0.31)	(0.31)
Critical Access Hospital	0.24	0.11	0.14	0.08	0.06
	(0.43)	(0.31)	(0.35)	(0.27)	(0.23)
Teaching	0.29	0.37	0.43	0.46	0.46
	(0.45)	(0.48)	(0.50)	(0.50)	(0.50)
Rural	0.21	0.09	0.09	0.05	0.04
	(0.40)	(0.29)	(0.29)	(0.22)	(0.19)
Number of hospitals	4,492	3,235	1,117	999	923

Notes: Open Payments columns summarize hospitals whose affiliated physicians received general, non-research, device-related payments during 2014-2017, before and after restricting to firms selling products in the focal device categories. Supply Guide columns summarize hospitals crosswalked from the Supply Guide data to American Hospital Association (AHA) Annual Survey data, before and after restricting to hospitals purchasing in the focal device categories. The analytic sample is the subset of hospitals in the "Supply Guide Focal Categories" column to which we were able to associate physicians in "relevant" specialties (defined in Section A.3) in the Medicare data.

Table A7: Payments, Sales, and Hospital Characteristics, by Device Category

		(1) AAA	(2) Atherectomy	(3) DES	(4) Hips	(5) Knees	(6) Shoulders	(7) Screws	(8) Spacers
Hospital count		472	695	619	889	883	823	746	692
Hospital-period count		2,660	4,050	3,666	5,138	5,114	4,580	4,282	4,006
Observations		10,640	24,300	10,998	20,552	20,456	36,640	29,974	28,042
Physician Payments									
All	$1[Pay_{chft} > 0]$ (%)	39	26	52	28	33	13	26	30
	$Pay_{chft}\|Pay_{chft} > 0$ ($)	461	65	66	216	296	119	138	91
		(1,756)	(658)	(417)	(869)	(1,263)	(611)	(506)	(416)
Meal	$1[Pay_{chft} > 0]$ (%)	39	25	50	26	31	11	24	28
	$Pay_{chft}\|Pay_{chft} > 0$ ($)	107	11	14	15	25	9	11	8
		(159)	(22)	(22)	(30)	(41)	(32)	(24)	(14)
Educ	$1[Pay_{chft} > 0]$ (%)	9	8	16	14	15	6	11	12
	$Pay_{chft}\|Pay_{chft} > 0$ ($)	667	51	66	116	157	61	68	46
		(2,266)	(368)	(322)	(255)	(375)	(175)	(167)	(108)
CHS	$1[Pay_{chft} > 0]$ (%)	4	3	7	5	5	3	5	5
	$Pay_{chft}\|Pay_{chft} > 0$ ($)	1,878	315	236	845	1,274	371	517	355
		(2,756)	(1,584)	(927)	(1,717)	(2,524)	(1,146)	(890)	(792)
Devices Purchases									
$1[Sales_{chft} > 0]$ (%)		52	39	65	61	60	25	42	41
$Sales_{chft}\|Sales_{chft} > 0$ ($)		30,916	1,175	11,222	12,376	19,198	1,962	5,287	3,411
		(72,157)	(4,675)	(20,231)	(33,902)	(59,815)	(10,522)	(18,376)	(10,775)
$Price_{chft}$ ($)		5,946	2,294	1,246	1,454	1,620	2,108	482	3,466
		(2,219)	(1,089)	(176)	(797)	(859)	(938)	(248)	(1,551)
Q_{cht}		21	3	28	39	59	8	74	8
		(27)	(5)	(29)	(68)	(113)	(19)	(103)	(11)
Top firm share (%)		78	73	76	76	76	80	73	70
		(19)	(21)	(19)	(20)	(20)	(21)	(22)	(22)
Other Hospital Characteristics									
Num. of relevant physicians		3	14	13	7	7	8	10	11
		(2)	(12)	(11)	(6)	(6)	(6)	(8)	(8)
Beds		416	352	365	293	293	309	333	343
		(264)	(248)	(252)	(246)	(247)	(251)	(251)	(253)
% Medicare		45	45	45	46	46	46	46	46
		(10)	(10)	(9)	(10)	(10)	(10)	(10)	(9)
% Medicaid		22	22	22	21	21	21	21	21
		(10)	(11)	(10)	(10)	(10)	(10)	(10)	(10)
Nonprofit (%)		83	81	82	82	83	82	82	81
Government (%)		13	12	12	11	11	11	11	11
Teaching (%)		63	54	55	47	47	49	52	54
Top AMC (%)		17	13	13	11	11	12	13	13

Notes: Pay_{chft} and $Sales_{chft}$ are average payments and sales per physician, respectively, at the category-hospital-firm-period level. Standard deviations of continuous variables shown in parentheses. Device payments and purchasing statistics are from authors' calculations using Open Payments and Supply Guide data, respectively.

Table A8: Association Between Physician Payments and Hospital Procurement at the Hospital Level

	(1)	(2)	(3)	(4)
Dependent Variable:	$1[Sales_{cht} > 0]$	$\log(Sales_{cht})$	$\log(Price_{cht})$	$\log(Q_{cht})$
$1[Pay_{chft} > 0]$	0.007	-0.007	-0.013	0.007
	(0.006)	(0.018)	(0.017)	(0.006)
$\log(Pay_{chft})$	-0.001	0.008*	0.006	0.003*
	(0.001)	(0.004)	(0.004)	(0.001)
Observations	33,496	29,859	29,859	29,859
R-squared	0.233	0.836	0.876	0.921
Dependent variable mean	0.905	11.656	4.218	7.473
	(0.293)	(1.646)	(1.784)	(0.775)

Notes: Authors' calculations using Open Payments and Supply Guide data. Extensive and intensive margin Pay_{chft} coefficient estimates based on the model presented in equation (1), when aggregated to the category-hospital-period level. Each column presents the results of a different regression for a specific dependent variable. Average category-hospital-period level price, $Price_{cht}$ is defined as the average of firm unit price at the category-hospital-firm-level, weighted by the number of units procured from each the firm. Observations are weighted by the inverse of the device category frequency, so that each device category receives equal weight in the regression. Standard errors clustered by firm-hospital-category in parentheses. ** p<0.01, * p<0.05.

Table A9: Association Between Physician Payments and Hospital Procurement, By Payment Type

		(1)	(2)	(3)	(4)	(5)
Dependent Variable:		$1[Sales_{chft} > 0]$	$\log(Sales_{chft})$	$\log(Price_{chft})$	Q_{chft}/Q_{cht}	$\log(Q_{cht})$
Meal	$1[Pay_{chft} > 0]$	0.023**	0.056**	0.003	0.006**	0.002
		(0.003)	(0.012)	(0.003)	(0.002)	(0.007)
	$\log(Pay_{chft})$	0.006**	0.024**	-0.000	0.005**	0.003
		(0.001)	(0.004)	(0.001)	(0.001)	(0.003)
Educ	$1[Pay_{chft} > 0]$	0.016**	-0.022	0.001	0.005	-0.021
		(0.006)	(0.018)	(0.005)	(0.003)	(0.013)
	$\log(Pay_{chft})$	-0.002	0.012*	0.001	0.001	0.002
		(0.002)	(0.005)	(0.001)	(0.001)	(0.003)
CHS	$1[Pay_{chft} > 0]$	0.004	-0.047	-0.012	0.002	0.024
		(0.013)	(0.039)	(0.011)	(0.006)	(0.025)
	$\log(Pay_{chft})$	0.001	0.020*	0.004	0.002	0.001
		(0.003)	(0.008)	(0.002)	(0.001)	(0.005)
Own	$1[Pay_{chft} > 0]$	0.023	0.004	0.013	-0.004	0.112*
		(0.022)	(0.082)	(0.017)	(0.011)	(0.046)
	$\log(Pay_{chft})$	-0.007*	-0.003	-0.002	0.001	-0.021*
		(0.003)	(0.013)	(0.003)	(0.002)	(0.009)
Observations		181,602	76,224	76,224	161,093	161,093
R-squared		0.673	0.830	0.922	0.828	0.858
D.V. mean and SD		0.480	8.498	7.429	0.207	2.392
		(0.500)	(1.858)	(0.842)	(0.310)	(1.657)

Notes: Authors' calculations using Open Payments and Supply Guide data. Extensive and intensive margin Pay_{chft} coefficient estimates based on the model presented in equation (1). Each column presents the results of a different regression for a specific dependent variable, where we include payment variables separately by type. Observations are weighted by the inverse of the device category frequency, so that each device category receives equal weight in the regression. Standard errors clustered by firm-hospital-category in parentheses. ** p<0.01, * p<0.05.

Table A10: Summary Statistics: Regression Covariates

Variable	Mean	S.D.
Hospital-Category level		
log(Total Medicare billing)	13.728	1.341
log(Physician count)	1.797	0.942
log(Beneficiaries per physician-service)	7.256	0.848
log(Physician work RVU)	0.280	0.498
Hospital Level		
log(Full time physicians and dentists)	2.306	1.990
Share Medicaid discharges	0.214	0.103
Share Medicare discharges	0.458	0.098
Integrated salary model hospital	0.431	0.495

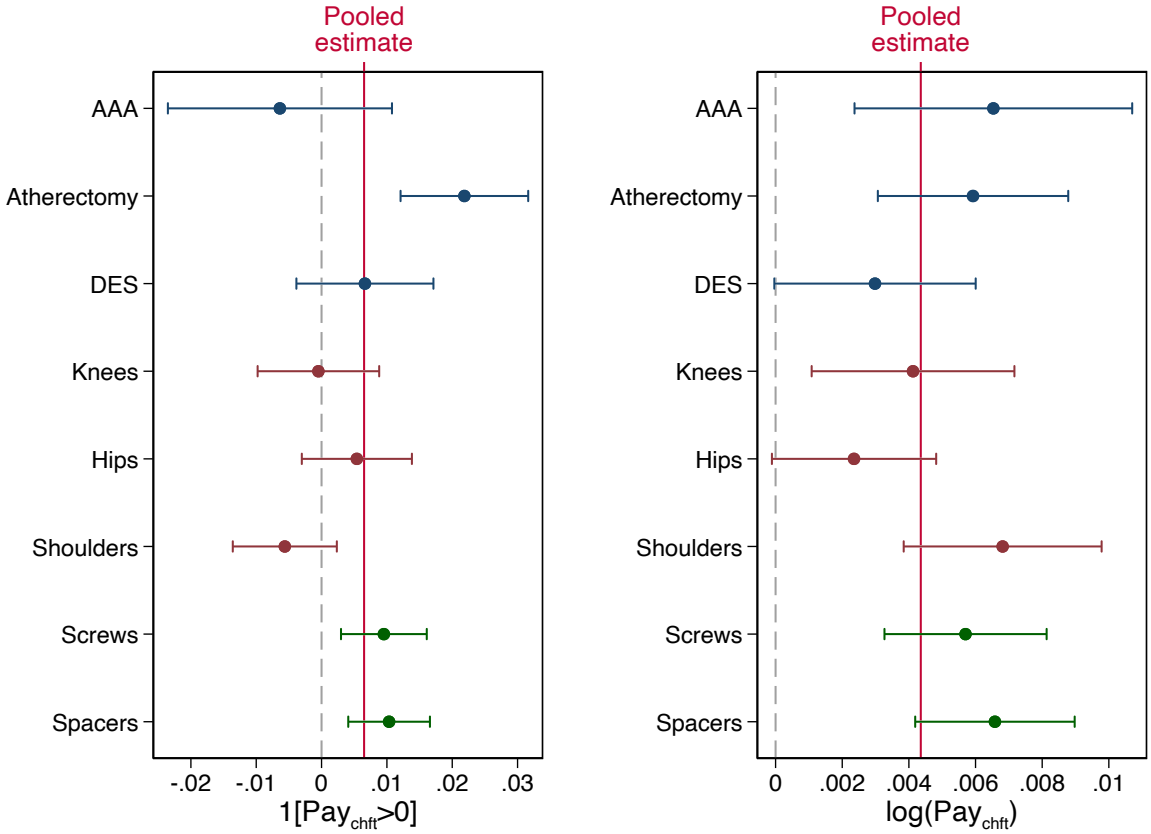
Notes: Sample average and standard deviation of the regression controls described in 2.1, weighting each device category equally. Sample statistics from 181,602 observations identifying a firm, category, hospital, and 6-month period.

Table A11: Probit Regression Coefficients

	Category interaction term							
	AAA	Atherectomy	DES	Hips	Knees	Shoulders	Screws	Spacers
log(Num. of relevant physicians)	0.243**	0.523**	0.198**	0.137**	0.152**	0.158**	0.165**	0.188**
	(0.064)	(0.057)	(0.059)	(0.051)	(0.052)	(0.055)	(0.058)	(0.059)
log(Physician work RVU)	-0.054	0.064	-0.131	0.065	0.096	0.074	0.049	0.011
	(0.073)	(0.101)	(0.130)	(0.067)	(0.068)	(0.073)	(0.082)	(0.088)
log(Physician beneficiary-days)	-0.300**	-0.386**	-0.605**	-0.507**	-0.498**	-0.563**	-0.515**	-0.550**
	(0.049)	(0.051)	(0.068)	(0.046)	(0.046)	(0.051)	(0.049)	(0.051)
% Medicare	-2.993**	-0.565	-1.260**	-0.905*	-0.900*	-1.113**	-1.156**	-1.144**
	(0.524)	(0.474)	(0.480)	(0.395)	(0.397)	(0.407)	(0.429)	(0.440)
% Medicaid	-0.685	1.175**	-0.411	-0.792*	-0.722*	-0.908*	-0.425	-0.344
	(0.410)	(0.347)	(0.378)	(0.347)	(0.354)	(0.371)	(0.374)	(0.390)
log(Beds)	0.226**	-0.005	0.165	0.277**	0.278**	0.229**	0.215**	0.233**
	(0.081)	(0.082)	(0.085)	(0.057)	(0.057)	(0.059)	(0.067)	(0.068)
Nonprofit	-1.310**	-0.762**	-0.518**	-0.782**	-0.798**	-0.902**	-0.690**	-0.782**
	(0.181)	(0.142)	(0.151)	(0.133)	(0.134)	(0.144)	(0.143)	(0.143)
Government	-0.669**	0.089	0.003	-0.225	-0.281	-0.312	-0.174	-0.271
	(0.195)	(0.157)	(0.169)	(0.150)	(0.151)	(0.163)	(0.161)	(0.161)
Teaching	1.800**	1.990**	1.954**	1.948**	1.928**	1.969**	1.792**	1.743**
	(0.193)	(0.246)	(0.229)	(0.160)	(0.161)	(0.167)	(0.163)	(0.163)
Intercept		-1.261	0.973	-0.547	-0.645	0.293	-0.223	-0.014
		(0.955)	(1.023)	(0.867)	(0.867)	(0.882)	(0.890)	(0.898)

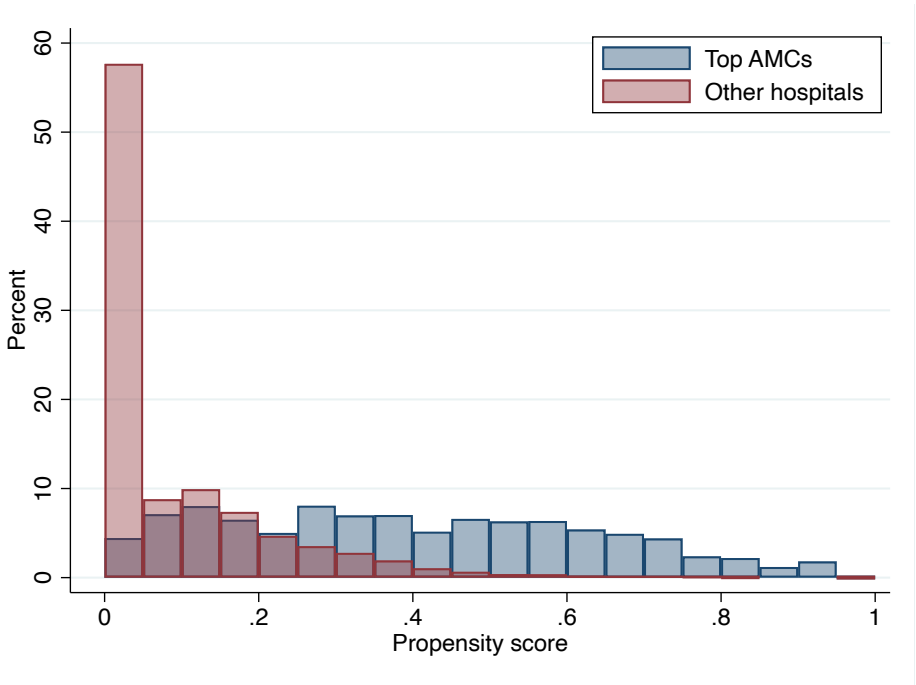
Notes: Coefficient estimates from a probit regression used to construct IPW used in estimating equation (2). Each variable (row) was interacted with a category indicator (column) to define a category-specific coefficient. Using 33,496 observations. Pseudo R-squared=0.357. Robust standard errors in parentheses. ** $p<0.01$, * $p<0.05$.

Figure A1: Association between Physician Payments and Q_{chft}/Q_{cht}, by Device Category



Notes: Authors' calculations using Open Payments and Supply Guide data. Category-specific extensive and intensive margin Pay_{chft} coefficient estimates, based on the model presented in equation (1), for the dependent variable Q_{chft}/Q_{cht}, controlling for hospital controls (with category-varying coefficients), category-firm-period, and category-hospital-firm fixed effects. Whiskers indicate the 95% CI for the coefficient. The vertical solid lines indicate the estimated analogous pooled coefficients reported in Table 2, column (4).

Figure A2: Propensity Score Distribution, by Expert Status



Notes: Propensity score prediction from a probit regression used to construct IPW used in estimating equation (2). Probit regression estimates are presented in A11.

Table A12: Association between Market Share, Top AMC Status, and Payments: Weighted Summary Statistics

	Top AMCs			Other Hospitals		
	All	Low/Zero Pay	High Pay	All	Low/Zero Pay	High Pay
Hospital count	88	68	67	640	587	395
Hospital-period count	518	250	268	3,669	2,528	1,141
Observations	2,013	970	1,043	14,277	9,865	4,412
Pay_{cht} ($1,000s)	0.27	0.01	0.75	0.20	0.01	0.63
	(1.16)	(0.02)	(1.84)	(1.06)	(0.03)	(1.82)
$Sales_{cht}$ ($1,000s)	37	32	49	40	36	48
	(69)	(63)	(81)	(88)	(88)	(88)
Num. of relevant physicians	10	7	16	8	7	11
	(11)	(7)	(13)	(7)	(6)	(10)
Physician work RVU	1.48	1.36	1.71	1.48	1.42	1.62
	(0.80)	(0.76)	(0.84)	(1.29)	(1.37)	(1.03)
Physician beneficiary-days	2,157	2,407	1,465	2,083	2,183	1,905
	(1,868)	(2,027)	(974)	(1,583)	(1,669)	(1,407)
% Medicare	45	47	42	46	46	45
	(10)	(10)	(9)	(10)	(10)	(10)
% Medicaid	21	20	22	21	22	21
	(11)	(11)	(10)	(9)	(9)	(9)
Beds	363	277	528	321	294	384
	(309)	(252)	(342)	(206)	(185)	(235)
Nonprofit (%)	87	90	80	71	68	78
Government (%)	11	8	17	10	9	11
Teaching (%)	100	100	100	45	40	58

Notes: Key hospital and hospital-category statistics by Top AMC status and Pay status, as defined in Section 4. All statistics are inverse-probability weighted, using a probit regression of $1[TopAMC_h]$ on log num. of relevant physicians, physician work RVU, log physician beneficiary-days, % Medicare, % Medicaid, log hospital beds, and hospital indicators for nonprofit, government, and teaching. The probit regression employs category-varying coefficients.

Table A13: Optimal Device Mix Regressions: Key Coefficient Estimates

	Unweighted		IPW-Weighted		Matched Sample	
Coefficient	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
$1[Pay_{chft} > 0]$	0.008*	0.004	0.009	0.006	0.008	0.005
$1[Pay_{chft} > 0] \times 1[NonTopAMC_h]$	-0.001	0.004	-0.007	0.008	-0.006	0.008
$\log(Pay_{chft})$	0.003**	0.001	0.003**	0.001	0.003*	0.001
$\log(Pay_{chft}) \times 1[NonTopAMC_h]$	0.002	0.001	0.003	0.002	-0.000	0.003
$1[Pay_{cht,-f} > 0]$	-0.003	0.004	-0.004	0.006	-0.003	0.004
$1[Pay_{cht,-f} > 0] \times 1[NonTopAMC_h]$	-0.001	0.004	0.002	0.006	0.011	0.007
$\log(Pay_{cht,-f})$	-0.002**	0.001	-0.003**	0.001	-0.002*	0.001
$\log(Pay_{cht,-f}) \times 1[NonTopAMC_h]$	0.001	0.001	0.002*	0.001	-0.000	0.001
$\eta_{Atherectomy,1} \times 1[NonTopAMC_h]$	0.014	0.012	0.020	0.022	0.065*	0.029
$\eta_{Atherectomy,2} \times 1[NonTopAMC_h]$	0.023*	0.010	0.014	0.010	-0.010	0.022
$\eta_{Atherectomy,3} \times 1[NonTopAMC_h]$	0.001	0.009	-0.001	0.010	-0.011	0.020
$\eta_{Atherectomy,4} \times 1[NonTopAMC_h]$	0.028**	0.008	0.039*	0.017	0.011	0.020
$\eta_{Hips,1} \times 1[NonTopAMC_h]$	-0.002	0.007	-0.007	0.008	0.011	0.023
$\eta_{Hips,2} \times 1[NonTopAMC_h]$	-0.008	0.008	0.017*	0.007	-0.002	0.024
$\eta_{Hips,3} \times 1[NonTopAMC_h]$	0.015*	0.007	-0.002	0.006	-0.001	0.022
$\eta_{Hips,4} \times 1[NonTopAMC_h]$	-0.003	0.005	-0.017**	0.005	-0.006	0.012
$\eta_{Knees,1} \times 1[NonTopAMC_h]$	-0.011	0.008	-0.009	0.008	-0.017	0.020
$\eta_{Knees,2} \times 1[NonTopAMC_h]$	0.025**	0.007	-0.006	0.008	0.012	0.018
$\eta_{Knees,3} \times 1[NonTopAMC_h]$	0.003	0.007	-0.037	0.050	-0.001	0.018
$\eta_{Knees,4} \times 1[NonTopAMC_h]$	-0.019**	0.006	0.053	0.050	-0.008	0.016
$\eta_{Shoulders,1} \times 1[NonTopAMC_h]$	0.009	0.012	-0.003	0.019	0.004	0.030
$\eta_{Shoulders,2} \times 1[NonTopAMC_h]$	-0.014	0.008	0.022	0.019	-0.032	0.023
$\eta_{Shoulders,3} \times 1[NonTopAMC_h]$	-0.005	0.009	0.013	0.008	-0.092**	0.030
$\eta_{Shoulders,4} \times 1[NonTopAMC_h]$	0.022**	0.008	-0.018	0.009	0.054*	0.023
$\eta_{Screws,1} \times 1[NonTopAMC_h]$	0.012	0.007	0.003	0.011	0.010	0.021
$\eta_{Screws,2} \times 1[NonTopAMC_h]$	0.001	0.008	0.012	0.012	-0.003	0.026
$\eta_{Screws,3} \times 1[NonTopAMC_h]$	0.011	0.006	0.007	0.011	0.004	0.019
$\eta_{Screws,4} \times 1[NonTopAMC_h]$	-0.012	0.007	0.008	0.010	-0.019	0.018
$\eta_{Spacers,1} \times 1[NonTopAMC_h]$	0.002	0.008	0.004	0.025	-0.003	0.025
$\eta_{Spacers,2} \times 1[NonTopAMC_h]$	0.009	0.009	0.026	0.020	-0.030	0.021
$\eta_{Spacers,3} \times 1[NonTopAMC_h]$	0.011	0.008	-0.043*	0.017	0.033*	0.016
$\eta_{Spacers,4} \times 1[NonTopAMC_h]$	0.008	0.007	0.036**	0.013	0.027	0.018
R-squared	0.818		0.844		0.890	
Observations	116,118		116,118		25,411	

Notes: Estimation results of the model presented in equation (2), absorbing category-firm-period fixed effects. Standard errors clustered by hospital-category in parentheses. ** p<0.01, * p<0.05.

Table A14: Association between Market Share, Top AMC Status, and Payments by Device Category

(a) Regression Estimates

	(1) AAA	(2) Atherectomy	(3) DES	(4) Hips	(5) Knees	(6) Shoulders	(7) Screws	(8) Spacers
$1[Pay_{chft} > 0]$	0.0324	0.0529	0.157**	0.101*	0.0610	0.0536	0.0387	0.0339
	(0.0261)	(0.0269)	(0.0314)	(0.0461)	(0.0384)	(0.0388)	(0.0230)	(0.0260)
$\log(Pay_{chft})$	0.0138**	0.0301**	0.0261**	0.0279**	0.0335**	0.0311**	0.0223**	0.0319**
	(0.00509)	(0.00590)	(0.00926)	(0.00685)	(0.00899)	(0.00943)	(0.00615)	(0.00838)
$[Pay_{chft} > 0] \times 1[NonTopAMC_h]$	-0.0564	0.0125	-0.0501	-0.0540	-0.0681	0.00843	0.0131	0.0196
	(0.0302)	(0.0276)	(0.0339)	(0.0511)	(0.0466)	(0.0418)	(0.0275)	(0.0325)
$\log(Pay_{chft}) \times 1[NonTopAMC_h]$	0.0189**	-0.00675	-0.0113	-0.000892	-0.00232	-0.00839	0.00908	0.00532
	(0.00623)	(0.00824)	(0.0106)	(0.00868)	(0.00950)	(0.0104)	(0.00706)	(0.00970)
$1[Pay_{cht,-f} > 0]$	-0.0189	-0.0760**	-0.0885**	-0.105*	-0.0670	-0.00550	0.0188	-0.00106
	(0.0131)	(0.0284)	(0.0212)	(0.0446)	(0.0383)	(0.0245)	(0.0239)	(0.0342)
$\log(Pay_{cht,-f})$	-0.0103**	-0.00327	-0.0206**	-0.0111**	-0.0182**	-0.0133**	-0.0132**	-0.0115**
	(0.00246)	(0.00394)	(0.00449)	(0.00405)	(0.00375)	(0.00334)	(0.00441)	(0.00317)
$[Pay_{cht,-f} > 0] \times 1[NonTopAMC_h]$	0.0257	0.0362	0.0165	0.0621	0.0550	-0.00859	-0.0229	0.000739
	(0.0162)	(0.0290)	(0.0234)	(0.0454)	(0.0398)	(0.0256)	(0.0283)	(0.0337)
$\log(Pay_{cht,-f}) \times 1[NonTopAMC_h]$	-0.00555	-0.00731	0.0108*	0.00327	0.00513	0.000397	-0.000326	-0.00680
	(0.00297)	(0.00443)	(0.00495)	(0.00439)	(0.00412)	(0.00372)	(0.00472)	(0.00367)
Observations	9,764	14,548	10,077	18,812	18,696	16,104	15,412	14,452
R-squared	0.534	0.254	0.246	0.194	0.182	0.128	0.157	0.104

(b) Distance from Benchmark (Top AMCs, No Payments)

	(1) AAA	(2) Atherectomy	(3) DES	(4) Hips	(5) Knees	(6) Shoulders	(7) Screws	(8) Spacers
Top AMCs, Low/Zero Pay	0.060**	0.063**	0.085**	0.132**	0.154**	0.042**	0.047**	0.043**
	(0.010)	(0.019)	(0.014)	(0.040)	(0.034)	(0.013)	(0.011)	(0.013)
Top AMCs, High Pay	0.117**	0.161**	0.206**	0.279**	0.284**	0.206**	0.162**	0.182**
	(0.020)	(0.035)	(0.045)	(0.044)	(0.041)	(0.043)	(0.034)	(0.037)
Other Hospitals, Low/Zero Pay	0.170**	0.268**	0.292**	0.192**	0.164**	0.175**	0.115**	0.084**
	(0.036)	(0.075)	(0.094)	(0.051)	(0.047)	(0.045)	(0.033)	(0.026)
Other Hospitals, High Pay	0.208**	0.311**	0.350**	0.269**	0.241**	0.225**	0.231**	0.230**
	(0.024)	(0.065)	(0.088)	(0.037)	(0.034)	(0.033)	(0.021)	(0.025)

Notes: Panel (a), each column represents a device category-specific OLS regression based on the model presented in equation 2 with category-interacted coefficients, where observations are inverse-probability weighted (IPW). IPW weights were constructed using a probit regression of $1[TopAMC_h]$ on log number of relevant physicians, physician work RVU, log physician beneficiary-days, % Medicare, % Medicaid, log hospital beds, and hospital indicators for non-profit, government, and teaching. The probit regression employs category-varying coefficients. Standard errors clustered by hospital in parentheses. Panel (b): Average distance from benchmark (Top AMCs with no payments) for each expertise/payment group and device category, derived from estimating Model 2 with category-interacted coefficients. Standard errors calculated using the delta method in parentheses. ** p<0.01, * p<0.05.

References

Agha, L. and Zeltzer, D. (2019). Drug diffusion through peer networks: The influence of industry payments. *NBER Working Paper*, No. 26338.

Anagol, S., Cole, S., and Sarkar, S. (2017). Understanding the advice of commissions-motivated agents: Evidence from the indian life insurance market. *Review of Economics and Statistics*, 99(1):1–15.

Annapureddy, A. R., Henien, S., Wang, Y., Minges, K. E., Ross, J. S., Spatz, E. S., Desai, N. R., Peterson, P. N., Masoudi, F. A., and Curtis, J. P. (2020). Association between industry payments to physicians and device selection in icd implantation. *JAMA*, 324(17):1755–1764.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic difference-in-differences. *American Economic Review*, 111(12):4088–4118.

Association of American Medical Colleges (2010). In the interest of patients: Recommendations for physician financial relationships and clinical decision making. Report of the task force on financial conflicts of interest in clinical care, Association of American Medical Colleges.

Baicker, K., Mullainathan, S., and Schwartzstein, J. (2015). Behavioral hazard in health insurance. *Quarterly Journal of Economics*, 130(4):1623–1667.

Bandiera, O., Best, M. C., Khan, A. Q., and Prat, A. (2021). The Allocation of Authority in Organizations: A Field Experiment with Bureaucrats*. *The Quarterly Journal of Economics*, 136(4):2195–2242.

Bandiera, O., Prat, A., and Valletti, T. (2009). Active and passive waste in government spending: Evidence from a policy experiment. *American Economic Review*, 99(4):1278–1308.

Baranek, B. and Titl, V. (2020). The cost of favoritism in public procurement.

Bedard, J., Moore, C. D., and Shelton, W. (2014). A survey of healthcare industry representatives' participation in surgery: some new ethical concerns. *Journal of Clinical Ethics*, 25(3):238–244.

Bergman, A., Grennan, M., and Swanson, A. (2021). Medical device firm payments to physicians exceed what drug companies pay physicians, target surgical specialists. *Health Affairs*, 40(4):603–612.

Bertrand, M., Bombardini, M., and Trebbi, F. (2014). Is it whom you know or what you know? an empirical assessment of the lobbying process. *American Economic Review*, 104(12):3885–3920.

Best, M. C., Hjort, J., and Szakonyi, D. (2019). Individuals and organizations as sources of state effectiveness. NBER Working Paper No. 23350.

Bhattacharya, V., Illanes, G., and Padi, M. (2020). Fiduciary duty and the market for financial advice. Working paper.

BMI Research (2020). *Industry forecast—United States medical devices forecast.* London: BMI Research.

Bosio, E., Djankov, S., Glaeser, E. L., and Shleifer, A. (2020). Public procurement in law and practice. *NBER Working Paper*, No. 27118.

Bronnenberg, B., Dube, J.-P., Gentzkow, M., and Shapiro, J. (2015). Do pharmacists buy Bayer? Informed shoppers and the brand premium. *Quarterly Journal of Economics*, 130(4):1669–1726.

Burgess, R., Jedwab, R., Miguel, E., Morjaria, A., and i Miquel, G. P. (2015). The value of democracy: Evidence from road building in Kenya. *American Economic Review*, 105(6):1817–51.

Burguet, R. and Che, Y.-K. (2004). Competitive procurement with corruption. *The RAND Journal of Economics*, 35(1):50.

Burke, L. G., Frakt, A. B., Khullar, D., Orav, E. J., and Jha, A. K. (2017). Association between teaching status and mortality in us hospitals. *JAMA*, 317(20):2105–2113.

Burke, L. G., Khullar, D., Orav, E. J., Frakt, A. B., and Jha, A. K. (2018). Do academic medical centers disproportionately benefit the sickest patients? *Health Affairs*, 37(6).

Carey, C. M., Lieber, E. M. J., and Miller, S. (2021). Drug firms' payments and physicians' prescribing behavior in Medicare Part D. *Journal of Public Economics*, 197.

Chan, D. C. and Dickstein, M. J. (2019). Industry input in policy making: Evidence from medicare. *Quarterly Journal of Economics*, 134(3):1299–1342.

Chatterji, A. K., Fabrizio, K. R., Mitchell, W., and Schulman, K. A. (2008). Physician-industry cooperation in the medical device industry. *Health Affairs*, 27(6):1532–1543.

Coviello, D. and Gagliarducci, S. (2017). Tenure in office and public procurement. *American Economic Journal: Economic Policy*, 9(3):59–105.

Craig, S. V., Grennan, M., and Swanson, A. (2021). Mergers and marginal costs: New evidence on hospital buyer power. *RAND Journal of Economics*, 52(1):151–178.

Decarolis, F., Fisman, R., Pinotti, P., and Vannutelli, S. (2020). Rules, discretion, and corruption in procurement: Evidence from italian government contracting. NBER Working Paper No. 28209.

DeJong, C., Aguilar, T., Tseng, C.-W., Lin, G. A., Boscardin, W. J., and Dudley, R. A. (2016). Pharmaceutical industry-sponsored meals and physician prescribing patterns for medicare beneficiaries. *JAMA Intern Med*, 176(8):1114–1122.

Di Tella, R. and Schargrodsky, E. (2003). The role of wages and auditing during a crackdown on corruption in the city of Buenos Aires. *Journal of Law and Economics*, 46(1):269–292.

Donald H. Taylor, J., Whellan, D. J., and Sloan, F. A. (1992). Effects of admission to a teaching hospital on the cost and quality of care for medicare beneficiaries. *New England Journal of Medicine*, 340(4):293–299.

Egan, M., Ge, S., and Tang, J. (2020). Conflicting interests and the effect of fiduciary duty – evidence from variable annuities. NBER Working Paper No. 27577.

Egan, M., Matvos, G., and Seru, A. (2019). The market for financial adviser misconduct. *Journal of Political Economy*, 127(1):233–295.

Farmer, B. (2018). Sales reps may be wearing out their welcome in the operating room. *National Public Radio*.

Flyvbjerg, B., Holm, M. K. S., and Buhl, S. L. (2008). How common and how large are cost overruns in transport infrastructure projects? *Transport Reviews*, 23(1):71–88.

Fujiwara, R. J., Shih, A. F., and Mehra, S. (2017). Cross-sectional Analysis of the Relationship between Paranasal Sinus Balloon Catheter Dilations and Industry Payments among Otolaryngologists. *Otolaryngology - Head and Neck Surgery (United States)*, 157(5):880–886.

Geweke, J., Gowrisankaran, G., and Town, R. J. (2003). Bayesian inference for hospital quality in a selection model. *Econometrica*, 71:1215–1238.

Grennan, M. (2013). Price discrimination and bargaining: Empirical evidence from medical devices. *American Economic Review*, 103(1):145–177.

Grennan, M. (2014). Bargaining ability and competitive advantage: Empirical evidence from medical devices. *Management Science*, 60(12):3011–3025.

Grennan, M., Myers, K., Swanson, A., and Chatterji, A. (2020). No free lunch? welfare analysis of firms selling through expert intermediaries. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3216172.

Grennan, M. and Swanson, A. (2020). Transparency and negotiated prices: The value of information in hospital-supplier bargaining. *Journal of Political Economy*, 128(4):1234–1268.

Grennan, M. and Town, R. J. (2020). Regulating innovation with uncertain quality: Information, risk, and access in medical devices. *American Economic Review*, 110(1):120–161.

Handel, B. R. and Schwartzstein, J. (2018). Frictions or mental gaps: What's behind the information we (don't) use and when do we care? *Journal of Economic Perspectives*, 32(1):155–178.

Hull, P. (2020). Estimating hospital quality with quasi-experimental data. *Working paper*.

Johns Hopkins Medicine (2021). Knee replacement alternatives to consider. https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/knee-replacement-alternatives-to-consider, accessed 11/20/2021.

Kang, K. (2016). Policy influence and private returns from lobbying in the energy sector. *The Review of Economic Studies*, 83(1).

Keeler, E. B., Rubenstein, L. V., Kahn, K. L., Draper, D., Harrison, E. R., McGinty, M. J., Rogers, W. H., and Brook, R. H. (1992). Hospital characteristics and quality of care. *JAMA*, 268(13):1709–1714.

Leon, M. B., Gada, H., and Fontana, G. P. (2014). Challenges and future opportunities for transcatheter aortic valve therapy. *Progress in Cardiovascular Diseases*, 56(6):635–645.

Levitt, S. D. and Syverson, C. (2008). Market distortions when agents are better informed: The value of information in real estate transactions. *Review of Economics and Statistics*, 90(4):599–611.

Lewis-Faupel, S., Neggers, Y., Olken, B. A., and Pande, R. (2016). Can electronic procurement improve infrastructure provision? evidence from public works in india and indonesia. *American Economic Journal: Economic Policy*, 8(3):258–283.

Lichand, G. and Fernades, G. (2019). The dark side of the contract: Do government audits reduce corruption in the presence of displacement by vendors? working paper.

Malmendier, U. and Schmidt, K. M. (2017). You owe me. *American Economic Review*, 107(2):493–526.

McGuire, T. (2000). *The handbook of health economics*, chapter Physician agency. Number 1. Amsterdam: Elsevier.

Mironov, M. and Zhuravskaya, E. (2016). Corruption in procurement and the political cycle in tunneling: Evidence from financial transactions data. *American Economic Journal: Economic Policy*, 8(2):287–321.

Mitchell, A. P., Trivedi, N. U., Gennarelli, R. L., Chimonas, S., Tabatabai, S. M., Goldberg, J., Jr., L. A. D., and Korenstein, D. (2021). Are financial payments from the pharmaceutical industry associated with physician prescribing?: A systematic review. *Annals of Internal Medicine*, 174(3):353–361.

Montgomery, K. and Schneller, E. (2007). Hospitals' strategies for orchestrating selection of physician preference items. *Milbank Quarterly*, 85(2):307–335.

O'Connor, B., Pollner, F., and Fugh-Berman, A. (2016). Salespeople in the surgical suite: Relationships between surgeons and medical device representatives. *PLoS One*, 11(8).

Okike, K., O'Toole, R. V., Pollak, A. N., Bishop, J. A., McAndrew, C. M., Mehta, S., 3rd, W. W. C., Garrigues, G. E., Harris, M. B., and Lebrun, C. T. (2014). Survey finds few orthopedic surgeons know the costs of the devices they implant. *Health Affairs*, 33(1):103–109.

Olken, B. A. (2007). Monitoring corruption: Evidence from a field experiment in indonesia. *Journal of Political Economy*, 115(2):200–249.

Rasul, I. and Rogger, D. (2018). Management of bureaucrats and public service delivery: Evidence from the nigerian civil service. *The Economic Journal*, 128(608):413–446.

Robles-Garcia, C. (2020). Competition and incentives in mortgage markets: The role of brokers. *Working paper*.

Rosenbaum, L. (2015). Reconnecting the dots—reinterpreting industry–physician relations. *New England Journal of Medicine*, 372(19):1860–1864.

Schneider, H. J. (2012). Agency problems and reputation in expert services: Evidence from auto repair. *Journal of Industrial Economics*, 60(3):406–433.

Schneller, E. S. (2009). The value of group purchasing - 2009: Meeting the need for strategic savings. *Health Care Sector Advances, Inc.*

Schulte, F. and Lucas, E. (2021). Device makers have funneled billions to orthopedic surgeons who use their products. Kaiser Health News.

Scott, K. W., Orav, E. J., Cutler, D. M., and Jha, A. K. (2017). Changes in hospital-physician affiliations in u.s. hospitals and their effect on quality of care. *Annals of Internal Medicine*, 166(1):1–8.

Shepard, M. (2021). Hospital network competition and adverse selection: Evidence from the massachusetts health insurance exchange. *American Economic Review*, forthcoming.

Smieliauskas, F. (2016). Conflicts of interest in medical technology markets: Evidence from orthopedic surgery. *Health Economics (United Kingdom)*, 25(6):723–739.

Steinbrook, R., Kassirer, J. P., and Angell, M. (2015). Justifying conflicts of interest in medical journals: A very bad idea. *BMJ*, 350:h2942.

Stern, A. D. (2017). Innovation under regulatory uncertainty: Evidence from medical technology. *Journal of Public Economics*, 145:181–200.

Yeh, J. S., Franklin, J. M., Avorn, J., Landon, J., and Kesselheim, A. S. (2016). Association of industry payments to physicians with the prescribing of brand-name statins in Massachusetts. *JAMA Internal Medicine*, 176(6):763–768.