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Alon Bergman
Matthew Grennan
Ashley Swanson

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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 the interactions that accompany them) 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. Payments are pervasive: 87 percent of device sales in our sample occurred at a hospital where a relevant physician received a payment from a device firm. Payments are also highly correlated with spending within a firm-hospital pair: event studies suggest that a large positive increase in payments to a given hospital from a given firm ($438 per physician on average, or 112 percent of the mean) is associated with 27 percent higher expenditures on the paying firm's devices post-event. Finally, we explore how payments mediate the relationship between expertise and device procurement patterns. Hospitals affiliated with the top Academic Medical Centers (AMCs), which plausibly represent an expert benchmark, purchase a different mix of devices than other hospitals, and payments to hospitals outside the top AMCs are correlated with larger deviations from the procurement patterns of top AMC hospitals.

Alon Bergman
University of Pennsylvania
alonberg@wharton.upenn.edu

Matthew Grennan
University of California, Berkeley
Haas School of Business
Berkeley, CA 94720
and NBER
mgrennan@berkeley.edu

Ashley Swanson
Graduate School of Business
Columbia University
3022 Broadway, Uris Hall 621
New York, NY 10027
and NBER
ats2180@gsb.columbia.edu

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 (Bandiera et al., 2009; Flyvbjerg et al., 2008). In others, the agency problem is exacerbated by selling firms influencing the agent, potentially leading to favoritism and other forms of corruption (Coviello and Gagliarducci, 2017; Di Tella and Schargrodsky, 2003; Lichand and Fernades, 2019; Mironov and Zhuravskaya, 2016). 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., Bandiera et al. 2021; Decarolis et al. 2020; Lewis-Faupel et al. 2016; Olken 2007; Rasul and Rogger 2018).[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; Farmer, 2018; O'Connor et al., 2016). Firms and physicians also have interactions involving consulting, technology development, and product testing, and many important 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 frequent 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

[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."

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 a range of physician and hospital costs 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 (Anagol et al., 2017; Bhattacharya et al., 2020; Egan et al., 2020, 2019; Grennan et al., 2020; Levitt and Syverson, 2008; Robles-Garcia, 2020; Schneider, 2012). 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: they choose what device to use in each procedure, and they influence hospitals to establish contracts with their preferred vendors.[4] Their device preferences are based on their subjective assessments of product 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 (Agha and Zeltzer 2019; Carey et al. 2021; DeJong et al. 2016; Grennan et al. 2020; Yeh et al. 2016).[6]

[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 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.

Far less attention has been paid to interactions between physicians and the device industry, with Annapureddy et al. (2020); Fujiwara et al. (2017); Smieliauskas (2016) 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 devices 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 the pharmaceutical payments literature to the device setting.

We present several new facts regarding industry payments and procurement outcomes for promoted medical devices, using a dataset that covers the top ten device categories in terms of payments.[8] First, within category-hospital, 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 associations are similar across a range of device categories, and are driven by hospitals shifting market shares across firms, rather than by expanding the total number of devices purchased or paying higher prices. The associations are also higher for the first dollar of payments than for any incremental dollar increase in payments, and are higher for the most commonly observed low-dollar meal-related payments than for relatively rare and lucrative education-, consulting/speaking-, or ownership-related payments.

Second, we estimate smaller, but still economically meaningful, correlations between payments and procurement outcomes within hospital-firm, suggesting that variation in device firm sales across hospitals in part reflects persistent preferences over firms. At the same time,

[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. This is consistent with our cross-sectional analysis of ICDs and other top categories, as described below.

[8]These categories account for 47 percent of device-related payments within our sample, and include cardiac, orthopedic, and neurosurgical devices.

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.

When we isolate the payment variation driven by large positive shocks to payment relationships between hospitals and firms, the estimated sales-payment elasticities more than triple. In other words, large increases in sales are contemporaneous with large increases in payments. This pattern is consistent with payments having a substantial causal impact on sales, though we cannot definitively rule out the possibility that both payments and sales are contemporaneously driven by another unobserved time-varying factor, including but not limited to other unobserved dimensions of hospital-firm interactions and taste shocks.

Lastly, we analyze whether payments are correlated with differences in the quality of device procurement. We use device market shares at top AMCs not receiving 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 whatever underlying mechanisms mediate the payment-procurement correlations documented in this paper, they 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 affiliated 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 (Bandiera et al., 2021; Bosio et al., 2020; Decarolis et al., 2020).

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 (Baranek and Titl, 2020; Best et al., 2019; Coviello and Gagliarducci, 2017). 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 the benchmark device mix suggest that payments may be 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-, consulting/speaking-, or ownership-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, in public sector procurement, and in political lobbying can be highly effective (Malmendier and Schmidt, 2017). Moreover, they are consistent with payments being proxies for device firm-physician interactions, rather than acting as simple 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 presumed 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) 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 server, and only aggregate statistics and regression coefficients were extracted by researchers.

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

[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).

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 ten top product categories, each with over $25 million in associated payments during 2014-2017. These include four cardiovascular products, five orthopedic products, and one neurosurgical product. 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; **DES** coronary stents, which are small tubes placed in blocked coronary arteries during angioplasty procedures; and implantable cardioverter defibrillators **(ICDs)**, which are battery-powered implants that detect and correct abnormal heart rhythms. 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. Finally, spinal cord stimulators **(SCS)** use mild electric currents to block nerve impulses and treat chronic pain. Overall, these device categories accounted for $1,246 million in payments, comprising 47 percent of Supply Guide-linked general payments to individual physicians, over 2014-2017.

[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.

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 77 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 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 ten 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 bins of total payments (across all firms) per relevant physician (in log scale), and present summary statistics for each bin in a separate column.

As shown in the top panel, we analyzed payments and utilization for 706 hospitals in the average device category and 69 percent of hospital-periods had affiliated physicians receiving

[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.

Table 1: Payments, Procurement Outcomes, and Hospital Characteristics

			$ per relevant physician (range)					
		All hospitals	[0]	$(0, 10]$	$(10, 100]$	$(100, 1K]$	$(1K, 10K]$	$10K <$
	Hospital count	706	418	353	449	302	82	16
	Hospital-period count	4,032	1,239	722	1,108	707	208	48
	Observations	20,211	6,236	3,738	5,437	3,414	1,144	242
	Physician Payments							
	Hospital-period payments ($1,000s)	7	0	0.04	0.42	4	36	409
		(62)	(0)	(0.05)	(1)	(6)	(45)	(429)
	Any hospital-period payments (%)	69	0	100	100	100	100	100
All	$1[Pay_{chft} > 0]$ (%)	33	0	30	45	57	66	62
All	$Pay_{chft} \| Pay_{chft} > 0$ ($)	392		3	20	130	880	10,835
		(5,497)		(3)	(21)	(178)	(1,483)	(24,866)
Meal	$1[Pay_{chft} > 0]$ (%)	31	0	29	43	54	62	58
Meal	$Pay_{chft} \| Pay_{chft} > 0$ ($)	27		3	14	32	45	54
		(69)		(3)	(16)	(56)	(100)	(166)
Educ	$1[Pay_{chft} > 0]$ (%)	11	0	3	11	28	38	38
Educ	$Pay_{chft} \| Pay_{chft} > 0$ ($)	135		2	21	90	259	3,528
		(879)		(2)	(20)	(123)	(604)	(11,734)
CHS	$1[Pay_{chft} > 0]$ (%)	5	0	0.38	2	14	31	28
CHS	$Pay_{chft} \| Pay_{chft} > 0$ ($)	617		3	26	197	972	4,092
		(1,601)		(2)	(22)	(189)	(1,223)	(6,596)
Own	$1[Pay_{chft} > 0]$ (%)	1	0	0.08	0.33	2	7	18
Own	$Pay_{chft} \| Pay_{chft} > 0$ ($)	6,529		2	26	213	2,040	22,718
		(27,354)		(2)	(25)	(223)	(2,218)	(37,990)
	Devices Purchases							
	Hospital-period sales ($1,000s)	293	136	259	310	420	577	639
		(446)	(240)	(373)	(428)	(526)	(599)	(787)
	$1[Sales_{chft} > 0]$ (%)	50	38	50	54	59	66	59
	$Sales_{chft} \| Sales_{chft} > 0$ ($)	10,932	10,892	8,789	10,403	11,402	13,899	14,002
		(38,400)	(48,050)	(25,822)	(34,360)	(32,821)	(36,451)	(42,162)
	$Price_{chft}$ ($)	4,790	4,684	4,729	4,837	4,857	4,922	5,540
		(5,742)	(5,675)	(5,681)	(5,785)	(5,746)	(5,802)	(6,624)
	Q_{cht}	24	24	21	23	27	33	30
		(60)	(72)	(47)	(51)	(61)	(68)	(53)
	$Q_{chft}/Q_{cht} \| Q_{chft} > 0$ (%)	42	53	42	39	36	33	35
		(33)	(36)	(33)	(32)	(30)	(28)	(32)
	Top firm share (%)	76	83	75	73	70	65	74
		(20)	(19)	(20)	(20)	(20)	(20)	(19)
	Other Hospital Characteristics							
	Num. of relevant physicians	10	5	10	11	13	14	15
		(9)	(5)	(7)	(9)	(12)	(11)	(13)
	Beds	342	239	347	371	422	431	441
		(253)	(184)	(230)	(253)	(284)	(278)	(274)
	% Medicare	46	47	46	46	44	44	42
		(10)	(11)	(9)	(9)	(10)	(10)	(9)
	% Medicaid	21	22	21	21	21	21	20
		(10)	(12)	(10)	(10)	(10)	(12)	(9)
	Nonprofit (%)	82	81	83	83	81	76	69
	Government (%)	12	11	12	12	14	17	28
	Teaching (%)	53	41	52	56	64	70	72
	Top AMC (%)	13	9	10	11	19	27	30

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. "Hospital-period payments" and "Hospital-period sales" are the average payments and sales, respectively, at the category-hospital-period level. 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.

some payments.[14] The distribution of payments was heavy-tailed: 6 percent of hospital-periods had payments of more than \$1,000 per relevant physician.

The second panel of Table 1 provides more detail on the patterns underlying the distribution of payments. Relevant physicians in the average hospital-period received about \$7,000 in payments across all firms in the average category, and hospital-periods in the top of the payment distribution received about \$409,000 across all firms. As shown in Appendix Table A7, the lowest average payments to sample hospitals were related to SCS implants (about \$1,000), and the highest average payments were related to knee implants (about \$19,000).

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 1 percent market share in the category.[15] This implies that there are (many) category-hospital-firm-periods with zero payments and/or zero sales. 33 percent of hospital-firm-period relationships involved payments, but this rate ranged from 30 percent in low-payment hospital-periods to 62 percent in high-payment hospital-periods. More strikingly, the average payment per physician for hospital-periods with nonzero payments was \$392 across all hospital-periods, but this varied from \$3 in low-payment hospital-periods to \$10,835 in high-payment hospital-periods. 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"); consulting fees, honoraria, and speaking fees ("CHS"); and royalty, licensing, and investment payments related to product development relationships ("Own"). As we look down the rows of Table 1 from "Meal" to "Educ" to "CHS" to "Own," the rate of hospitals receiving each type of payment from a selling firm decreases steadily (from 31 percent for meals, to 1 percent for royalties/ownership) and the dollar value per *paid* hospital increases dramatically (from \$27 per physician for meals to \$6,529 per physician for royalties/ownership). The high-payment hospital-periods were those receiving rare, but highly lucrative CHS and royalties/ownership 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

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

[15] The total market share of excluded small firms was 5.16 percent in the average category.

ten focal device categories. The average hospital-category-period involved sales of $293,960 across all firms, with device sales increasing monotonically across the bins of the payment distribution. This positive correlation is consistent with device firms targeting ex ante high-volume hospitals for payments, and/or with a causal effect of payments on procurement.

The next set of rows summarize 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, 50 percent of included hospital-firm-periods had positive sales (i.e., an observed 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 $10,932. These contracting relationships were for high-priced devices used in specialized procedures; hence, the average quantity sold per hospital-period was only 24 units per physician and the average unit price was $4,790. Price variability is substantial, with the standard deviation exceeding the mean across all bins of the payment distribution.

The average firm had a market share of 42 percent, conditional on having a positive market share. 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 76 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 10 affiliated relevant physicians, had 342 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 and royalties/ownership 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 the 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 A8 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 $f_i(p\vec{a}y_j)$ 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 $f_i(p\vec{a}y_j)$ and η_{ij}^{de}. For example, $f_i(p\vec{a}y_j) = -\eta_{ij}^{de}$ 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 $f_i(p\vec{a}y_j) = \delta \sum p\vec{a}y_j$ would model a case where all payment dollars influence the doctor's decisions, increasing the propensity to choose the device at the rate $\delta > 0$.[16] 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 $f_i(p\vec{a}y_j)$ and its relationship with several key dependent variables: device choice, which reflects physicians' preferences 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

[16] 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 $\delta \sum p\vec{a}y_j$ represents the agent's manipulation of the value of option j given bribes of value $p\vec{a}y_j$.

mix, where arguably the decision error η_{ij}^{de} is minimized.

3 Associations between Payments and Device Spending

This Section extends the correlations documented in Table 1 to a regression analysis framework, controlling for several dimensions of unobserved heterogeneity and exploring different mechanisms and margins. As noted previously, nonrandom selection of physicians into receiving payments presents a challenge for identification of causal effects of payments (and the interactions/relationships they proxy for) on device procurement outcomes. For these reasons, we use fixed effect and event study regressions with varying levels of controls for unobserved hospital preferences in order to shed light on the mechanisms underlying the association between payments and procurement.

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}.[17] In all specifications, we control for device category-firm-period fixed effects θ_{cft} in order to 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. For the most part, we present pooled results in the main text and category-by-category results in the Appendix. The pooled regression specification is:

$$y_{chft} = \delta^e 1[Pay_{chft} > 0] + \delta^i \log(Pay_{chft}) + X_{chft} * \beta + \theta_{cft} + \epsilon_{chft} \tag{1}$$

Table 2 summarizes the results of these regressions. We first discuss the results for our baseline choice of controls, category-hospital fixed effects (odd-numbered columns), which control for the time-invariant component of unobserved hospital factors that impact hospital procurement, such as reputation, policy environment, and patient population size and severity, within each device category. Thus, these results focus on firm-hospital-specific variation around hospital-category means. The main threat to a causal interpretation of these conditional correlations will thus be the extent to which specific firms 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

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

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. In the end of the section, we turn to results using category-hospital-firm fixed effects, which leverage variation over time within hospital-firm relationships (even-numbered columns).

First, we focus on panel (a) of Table 2. Column (1) shows a statistically significant and economically meaningful relationship between whether a hospital buys from a given firm ($1[Sales_{chft} > 0]$) and both the existence and dollar value of payments from that firm to physicians performing surgeries at the hospital. The estimates indicate that a firm providing the mean level of payments ($392 per physician) to a given hospital, vs. no payments, is associated with a 24 percentage point higher probability the hospital purchases from that firm (a 72 percent change, given the mean probability of 33 percent).[18] About half of this association is driven by the mere existence of the payment relationship (i.e., the increase from $0 to $1 in payments has a larger association than any subsequent $1 increase in payments).

Column (3) shows that, for the sample of observations with nonzero sales, the positive association with payments extends to the dollar amount of $Sales_{chft}$. The estimates indicate that the mean level of payments (vs. no payments) is associated with 162 percent higher sales. Columns (5)-(9) decompose this relationship, indicating that, relative to a hospital-firm pair with no payments, a hospital-firm pair with mean payments would be associated with a 4 percent higher negotiated price (column 5), and a 152 percent higher market share (conditional on purchasing) (column 7). Column (9) indicates that payments are not associated with higher purchasing *at the hospital level*. 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 (Baranek and Titl, 2020; Best et al., 2019; Coviello and Gagliarducci, 2017), or with increased volumes of (potentially unnecessary) procedures of the type highlighted in the popular press (Schulte and Lucas, 2021).

The relatively modest relationship 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.

[18] For each of the calculations in this Section, we combine the coefficient on having any payment with the coefficient on the payment dollar value. That is, we evaluate $\hat{\delta}^e 1[Pay_{chft} > 0] + \hat{\delta}^i \log(Pay_{chft})$ at the mean of Pay_{chft}, for each set of $(\hat{\delta}^e, \hat{\delta}^i)$ estimates.

Table 2: Association Between Physician Payments and Hospital Procurement

(a) Using Total Payment Value

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:		$1[Sales_{chft} > 0]$		$\log(Sales_{chft} > 0)$		$\log(Price_{chft})$		$\log(Q_{chft}/Q_{cht})$		$\log(Q_{cht})$
Fixed Effects:		cft+ch	cft+chf	cft+ch	cft+chf	cft+ch	cft+chf	cft+ch	cft+chf	ct+ch
All	$1[Pay_{chft} > 0]$	0.113**	0.032**	0.169**	0.034**	0.006	-0.003	0.164**	0.031**	0.008
		(0.004)	(0.003)	(0.015)	(0.011)	(0.004)	(0.004)	(0.014)	(0.009)	(0.016)
	$\log(Pay_{chft})$	0.022**	0.003**	0.133**	0.019**	0.006**	0.001	0.127**	0.016**	0.003
		(0.001)	(0.001)	(0.004)	(0.003)	(0.001)	(0.001)	(0.004)	(0.002)	(0.003)
Observations		202,108	202,108	91,287	87,580	91,287	87,580	91,287	87,580	35,705
R-squared		0.367	0.657	0.547	0.822	0.908	0.953	0.357	0.811	0.876

(b) Using Payments Broken Down by Type

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:		$1[Sales_{chft} > 0]$		$\log(Sales_{chft} > 0)$		$\log(P_{chft})$		$\log(Q_{chft}/Q_{cht})$		$\log(Q_{cht})$
Fixed Effects:		cft+ch	cft+chf	cft+ch	cft+chf	cft+ch	cft+chf	cft+ch	cft+chf	ct+ch
Meal	$1[Pay_{chft} > 0]$	0.112**	0.027**	0.238**	0.046**	0.008	-0.001	0.227**	0.036**	0.009
		(0.004)	(0.003)	(0.015)	(0.011)	(0.004)	(0.004)	(0.013)	(0.008)	(0.015)
	$\log(Pay_{chft})$	0.021**	0.005**	0.102**	0.019**	0.006**	-0.000	0.095**	0.018**	0.006
		(0.001)	(0.001)	(0.005)	(0.004)	(0.001)	(0.001)	(0.005)	(0.003)	(0.004)
Educ	$1[Pay_{chft} > 0]$	0.031**	0.017**	0.076**	-0.024	0.000	-0.000	0.095**	-0.001	-0.041*
		(0.006)	(0.005)	(0.022)	(0.017)	(0.005)	(0.004)	(0.021)	(0.013)	(0.017)
	$\log(Pay_{chft})$	0.002	-0.003	0.024**	0.013**	0.001	0.001	0.022**	0.009**	0.002
		(0.002)	(0.001)	(0.006)	(0.004)	(0.001)	(0.001)	(0.005)	(0.003)	(0.004)
CHS	$1[Pay_{chft} > 0]$	0.010	-0.002	-0.110*	-0.037	-0.014	-0.006	-0.089	-0.006	0.037
		(0.013)	(0.012)	(0.049)	(0.035)	(0.011)	(0.009)	(0.045)	(0.027)	(0.031)
	$\log(Pay_{chft})$	0.010**	0.002	0.106**	0.018*	0.008**	0.002	0.097**	0.008	-0.001
		(0.003)	(0.002)	(0.010)	(0.007)	(0.002)	(0.002)	(0.009)	(0.005)	(0.006)
Own	$1[Pay_{chft} > 0]$	0.079**	0.016	-0.010	0.016	0.011	0.007	-0.067	-0.063	0.180**
		(0.023)	(0.021)	(0.097)	(0.063)	(0.023)	(0.013)	(0.092)	(0.057)	(0.048)
	$\log(Pay_{chft})$	0.000	-0.004	0.093**	-0.003	-0.000	-0.002	0.099**	0.008	-0.023*
		(0.003)	(0.003)	(0.016)	(0.010)	(0.004)	(0.002)	(0.015)	(0.009)	(0.009)
Observations		202,108	202,108	91,287	87,580	91,287	87,580	91,287	87,580	35,705
R-squared		0.367	0.657	0.547	0.822	0.908	0.953	0.357	0.811	0.876

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). Within each panel, each column presents the results of a different regression, for a specific dependent variable and set of included fixed effects. For each dependent variable and fixed effects combination, we estimate one model where we use total payments per physician as the treatment variable (panel a), and another model where we include payment variables separately by type (panel b). 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.

The strong conditional correlation between payments to physicians and market share of the paying device firm at a given hospital could be due to a variety of factors. To begin to shed more light on the matter, Panel (b) of Table 2 performs the same regressions just discussed, but with payments broken down by type. For the correlations with market share (column 7), this exercise demonstrates that the results regarding overall payments are mostly driven by meal payments. For example, the coefficients on education-related payments are statistically significant, but the extensive margin payment coefficient on $1[Pay_{chft} > 0]$ is 42 percent the size of the analogous meal-payment coefficient. Similarly, the intensive margin payment coefficient on $\log(Pay_{chft})$ for education payments is 23 percent the size of the analogous meal-payment coefficient. CHS and ownership payments exhibit similarly smaller coefficient magnitudes, and this general result extends to the other dependent variables we examine. Paired with their lower frequencies and larger magnitudes in dollars, this suggests a smaller role for non-meal payments on average in driving any associations with sales.

We next turn to the regressions with category-hospital-firm fixed effects in the even numbered columns, which focus on variation in payments and procurement outcomes over time within hospital-firm pairs. This change mutes the correlations between payments and sales substantially. For example, the estimates indicate that the mean level of payments (vs. no payments) is associated with a 5 percentage point higher likelihood of the hospital purchasing the promoted product (column 2), and with 16 percent higher sales among hospital purchasers (column 4). This is consistent with the more saturated fixed effects controlling for positive bias from unobserved hospital-firm specific preferences, or with the richer fixed effects introducing attenuation bias if small fluctuations in payments within a highly persistent physician-firm relationship reflect noise rather than systematic shocks to physician-firm interactions. Our conversations with industry participants suggest that both factors may be present, and we explore the issue further in a series of event studies below. However, even these smaller coefficients reflect economically meaningful associations between payments and procurement outcomes.

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. Finally, it is primarily driven by meal payments. 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.

The results in Table 2 estimate pooled coefficients on payments across the ten medical device categories in our data. Figure 1 sheds more light on how these associations vary across device categories. The left and right panels show the coefficients and 95 percent confidence intervals on $1[Pay_{chft} > 0]$ and $\log(Pay_{chft})$, respectively, in separate estimations of equation (1), within each device category, controlling for the richest set of fixed effects in Table 2. The dependent variable is $\log(Sales_{chft})$; analogous results for $1[Sales_{chft} > 0]$ are shown in Appendix Figure A1. The extensive margin coefficients on $1[Pay_{chft} > 0]$ range from -0.002 to 0.057, and all but three coefficients (AAA stent/grafts, ICDs, and shoulder implants) are positive. The intensive margin coefficients on $\log(Pay_{chft})$ range from -0.0498 to 0.107, and all but one coefficient (ICDs) are positive. As expected, these specifications are estimated less precisely than the pooled specification. However, the coefficient estimates are clustered fairly closely to the pooled estimates, particularly for the $\log(Pay_{chft})$ coefficients, suggesting that the relationships between payments and device procurement are similar across a range of device categories with different associated specialties and different frequencies of usage.

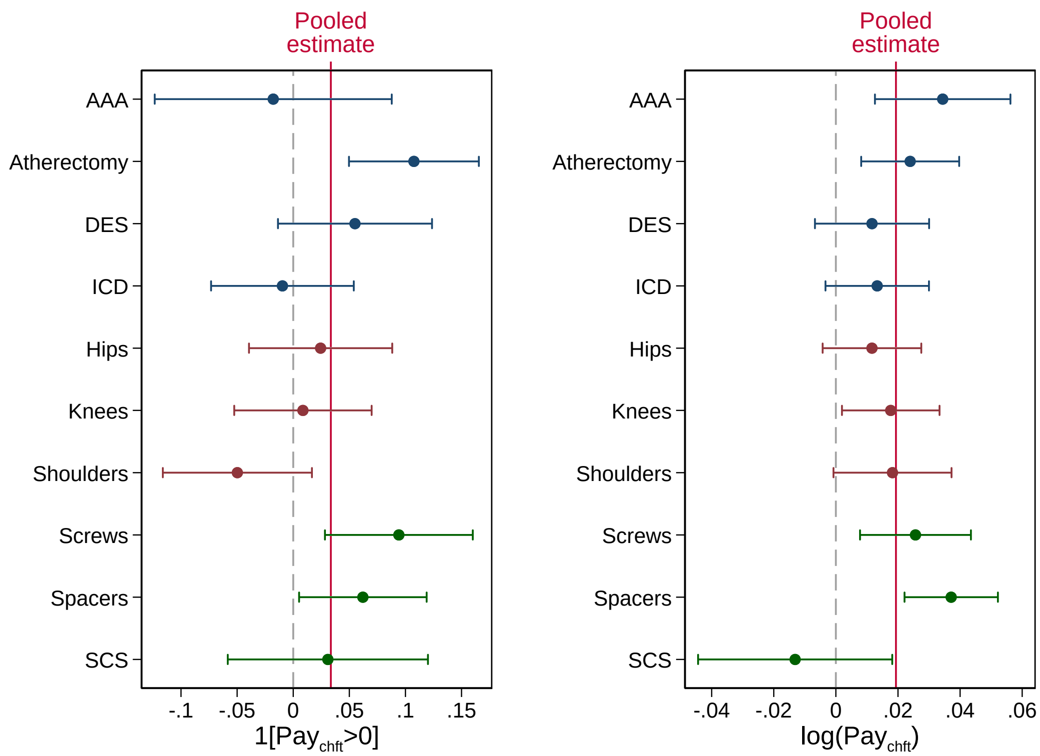
3.1 Payment shocks

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.[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

[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.

Figure 1: Association between Physician Payments and $\log(Sales_{chft})$, 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 $\log(Sales_{chft})$, controlling for hospital controls (with category-varying coefficients), category-firm-period fixed effects, 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).

$[\tau - t_{pre}, \tau + t_{post}]$; average pre-event payments for $ch'f'$ were in the lower third of the payment distribution across hospital-firm-periods in category c:

$$\left(\frac{1}{t_{pre}} \sum_{t'=\tau - t_{pre}}^{\tau - 1} Pay_{ch'f't'} < P_{33.3\%}(Pay_{chft} | Pay_{chft} > 0) \right);$$

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

$$\left(\frac{1}{t_{post} + 1} \sum_{t'=\tau}^{\tau + t_{post}} Pay_{ch'f't'} > P_{66.7\%}(Pay_{chft} | Pay_{chft} > 0) \right).$$

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 $max_{f't'}\{Pay_{ch'f't'}\} < P_{33.3\%}(Pay_{chft} | Pay_{chft} > 0)$. We include all firms within each control category-hospital in the regression sample.

With the above definitions in hand, we estimate:

$$y_{chft} = \theta_{r(\tau(chf),t)} + X_{chft} * \beta + \theta_{cft} + \epsilon_{chft} \tag{2}$$

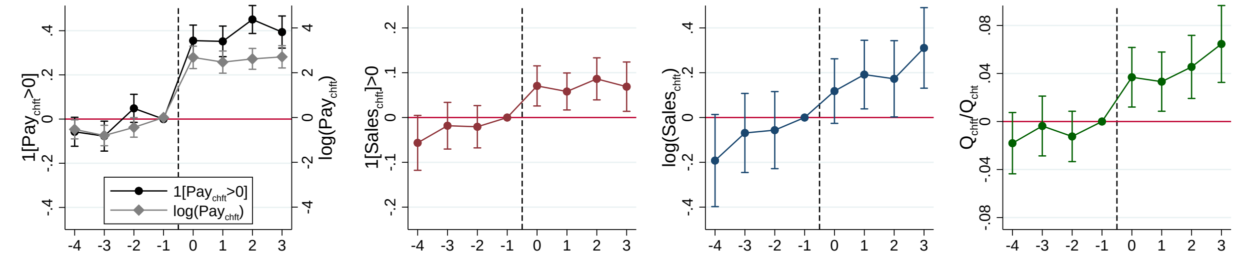
where $\theta_{r(\tau(chf),t)}$ is a set of dummies for the timing of calendar half-year t relative to combination chf's event period τ_{chf}. The hold-out period is $\tau_{chf} - 1$. We present results for several different dependent variables y_{chft}: we show $1[Pay_{chft} > 0]$ and $log(Pay_{chft})$ to give a sense of the magnitudes and dynamics of the payment shocks; we then analyze the dependent variables from our previous analyses $(1[Sales_{chft} > 0], \log(Sales_{chft}), Q_{chft}/Q_{cht})$.[20] As in the previous Section, we interact all controls with category dummies, and control for category-firm-period and category-hospital-firm fixed effects.

In Figure 2, 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. In Appendix Figure A2, we present two alternative windows: $(t_{pre}, t_{post}) = (4, 1)$ (two years pre-event, one year post-event) and $(t_{pre}, t_{post}) = (2, 3)$ (one year pre-event, two years post-event). The shorter time horizons allow for larger samples of hospitals whose payment shocks occurred between the second half of 2014 and the second half of 2016.

Focusing first on the first stage estimates in the left column of each panel, we see that the average event was associated with 36 percent of treated category-hospital-firms initiating a

[20]To combine both extensive margin and intensive margin sales relationships in the market share variable, Q_{chft}/Q_{cht} includes zeros in these analyses.

Figure 2: Event Study



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 sample includes 28 event hospitals, and 172 control hospitals, in the average category. This results in 50,200 observations total for dependent variable (d.v.) $1[Pay_{chft} > 0]$, 3,625 observations for d.v. $\log(Pay_{chft})$, 50,200 observations for d.v. $1[Sales_{chft} > 0]$, 16,277 observations for d.v. $\log(Sales_{chft})$, and 47,265 observations for d.v. Q_{chft}/Q_{cht}.

payment relationship (primary axis), and with a 263 percent increase in Pay_{chft} (conditional on $Pay_{chft} > 0$) (secondary axis). That is, payment shocks involved both intensive and extensive margin increases in payments. 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 in the right three panels of Figure 2. From left to right, the event studies indicate that, relative to pre-event averages and to control hospitals, event hospitals were 9.4 percentage points more likely to purchase the event firm's devices post-event; had 27 percent higher expenditures on the event firm's devices post-event; and devoted 5.2 percentage point higher market shares to the event firm post-event.

The point estimates in these figures suggest some potential positive pre-trends in usage leading up to the changes in payments. These are most pronounced for the $\log(Sales_{chft})$ regression, which is identified from the relatively small number of observations with positive hospital-firm-category-level sales both pre- and post-event. While they are not statistically significant in the full support sample, they are significant in some subsamples reported in Appendix Figure A2. We interpret these as cautioning against a strict interpretation of payments leading to usage. This pattern could relate to some degree of codetermination by a third unobserved factor, or relatedly, to payments being a noisy proxy for a broader set of industry interactions taking place around the same time.

Appendix Figure A2 shows that these patterns are similar in analyses with smaller event windows and larger sample sizes. Appendix Figure A3 shows that the patterns in payments and sales observed for overall payment shocks are most similar to the analogous patterns observed when we focus explicitly on shocks to meal payments.[21] A similar pattern in device sales relative to the event date is also present for education-related payments, though it is flatter overall. The patterns are much noisier when we focus on CHS and ownership payment shocks, reflecting that there are very few such events in any given category.

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. To show this more precisely, Appendix Table A9 uses the "first stage" relationship between the shock and $\log(Pay_{chft}+1)$ to scale the "reduced form" relationship between the shock and different sales dependent variables.[22] It also shows the analogous TWFE relationship between $\log(Pay_{chft}+1)$ and sales in the full sample from Table 2 above, and in the event study sample specifically. Whether we focus on $1[Sales_{chft} > 0]$ or $\log(Sales_{chft})$, the "elasticity" of the association between sales and payments is approximately 3.6 times as large when we focus on payment variation involving large shocks, relative to all payment variation in our full sample.

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

[21] In the event study regressions focusing on shocks to a given payment type, we control for both the extensive margin and also the intensive margin variables of all other payment types, but do not report those coefficients.

[22] Here, we combine the intensive and extensive margins of payments into a single variable to facilitate comparison across regressions.

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 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 (Burke et al., 2017, 2018; Keeler et al., 1992; Donald H. Taylor et al., 1992), 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, 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:[23]

$$\begin{aligned} Q_{chft}/Q_{cht} = \; & \delta_1^e 1[Pay_{chft} > 0] + \delta_2^e 1[Pay_{chft} > 0] * 1[NonTopAMC_h] \\ & + \delta_1^i \log(Pay_{chft}) + \delta_2^i \log(Pay_{chft}) * 1[NonTopAMC_h] \\ & + X_{chft} * \beta + \theta_{cft} + \eta_{cf} * 1[NonTopAMC_h] + \epsilon_{chft}. \end{aligned} \tag{3}$$

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

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

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 (δ_1^e, δ_1^i) and (δ_2^e, δ_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 (3) with our standard weighting scheme,[24] we used two 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 (3) using inverse probability weights (IPWs) resulting from this regression.[25] IPW-weighted summary statistics for each hospital type are presented in Appendix Table A11; 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 (3) while controlling for match group fixed effects. Appendix Table A12 presents the results of estimating three versions of equation (3): unweighted, IPW-weighted, and matched sample.

Panel (b) of Table 3 summarizes the estimates of equation (3) 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

[24]Weighting each of the ten focal device categories equally so that each of the statistics below should be interpreted as applying *within the average focal device category*.

[25]The distributions of the resulting propensity scores are presented in A4. 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.

of the vector of market shares predicted by equation (3), 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 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 4.9 times further away from the benchmark than low/zero pay Top AMC hospitals. Among non-Top AMC hospitals, high pay hospitals were 1.6 times further away from the benchmark than low/zero pay non-Top AMC hospitals. As can be seen in Appendix Table A12, 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.

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

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	86	66	63	621	565	372
Hospital-period count	503	248	256	3,528	2,441	1,087
Observations	1,877	914	963	13,203	9,152	4,051
Pay_{cht} (\$1,000s)	1.27	0.01	2.26	0.44	0.01	1.40
	(6.32)	(0.03)	(8.32)	(6.86)	(0.02)	(12.17)
$Sales_{cht}$ (\$1,000s)	44	40	48	42	39	47
	(84)	(89)	(78)	(94)	(94)	(93)
Num. of relevant physicians	16	12	20	9	8	11
	(14)	(11)	(16)	(8)	(6)	(9)
Physician work RVU	1.79	1.65	1.92	1.49	1.46	1.57
	(0.97)	(1.02)	(0.90)	(1.27)	(1.36)	(1)
Physician beneficiary-days	1,229	1,311	1,158	2,115	2,101	2,132
	(1,066)	(1,205)	(883)	(1,567)	(1,560)	(1,576)
% Medicare	39	39	38	47	47	46
	(9)	(10)	(8)	(9)	(9)	(9)
% Medicaid	27	27	26	21	21	20
	(13)	(15)	(10)	(10)	(10)	(9)
Beds	581	499	653	307	281	366
	(382)	(390)	(356)	(206)	(189)	(228)
Nonprofit (%)	63	63	64	85	84	86
Government (%)	32	32	32	9	9	9
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	0.117**	0.047**	0.188**	0.152**	0.119**	0.227**
	(0.007)	(0.003)	(0.010)	(0.008)	(0.009)	(0.007)
IPW-weighted	0.109**	0.046**	0.225**	0.202**	0.172**	0.273**
	(0.009)	(0.005)	(0.018)	(0.018)	(0.020)	(0.016)
Matched hospitals	0.117**	0.050**	0.182**	0.179**	0.130**	0.228**
	(0.011)	(0.006)	(0.016)	(0.010)	(0.012)	(0.011)

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 (3) using three alternative weighting approaches. Standard errors calculated using the delta method in parentheses. ** p<0.01, * p<0.05.

is a novel merger of two administrative data sets on ten 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 the majority of hospitals having affiliated physicians who received some payment. 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.

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.[26] 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

[26]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).

on the device development.

An important limitation of our study is that our analysis is focused on device categories that are technologically "mature".[27] 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.[28] Such a process likely necessitates significant interactions 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.

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

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

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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.[29] 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.[30]

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

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

[30] For comparison, directly using each payment's product description will only classify 82 percent of all individual payments, or 83 percent of total payment dollars.

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.

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).[31] 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.[32]

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).[33] 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™ 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

[31] 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.

[32] 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.

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

Table A2: Identifying Payments' UMDNS Codes

			Payment Count		Total Payment Value ($mil)	
Step	Procedure	Objs. IDed (Cum.)	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.

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. 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.[34] 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.

[34] 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.

- **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.[35] These algorithmic matches are accepted if an object matches to a unique UMDNS code in the Supply Guide data.

- **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.[36] We then manually flagged word-pairs that represent device categories. We identified 174 such pairs.[37] 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.[38]

[35] 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 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."

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

[37] 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.

[38] For example, if all previously-identified payments made by a firm to orthopedists are related to knees

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."

and hips, we would assume that any "product portfolio" payments made by the firm to orthopedists are only related to knees and hips.

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	3.64	3.42
Orthopedics, Joints, Knee and Hip, *Knees*	**82.58**	**6.67**	**5.82**	**288.50**	**10.80**	**10.15**
Orthopedics, Spine, *Screws*	**64.56**	**5.21**	**4.55**	**305.62**	**11.44**	**10.75**
Orthopedics, Joints, Knee and Hip, *Hips*	**52.11**	**4.21**	**3.67**	**187.75**	**7.03**	**6.61**
Orthopedics, Spine, *Spacers*	**47.07**	**3.80**	**3.32**	**163.96**	**6.14**	**5.77**
Heart and Vascular, Cardiac, Valves, Transcatheter, TAVR	42.11	3.40	2.97	63.62	2.38	2.24
Heart and Vascular, Cardiac, Rhythm, *ICD*	**37.08**	**2.99**	**2.62**	**45.13**	**1.69**	**1.59**
Pain Mgmt, Spinal Cord *SCS*	**36.95**	**2.98**	**2.61**	**41.16**	**1.54**	**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**	**2.03**	**1.90**
Orthopedics, Joints, Suture Anchors	30.67	2.48	2.16	122.14	4.57	4.30
Orthopedics, Joints, Extremities, Shoulder and Elbow, *Shoulders*	**28.41**	**2.29**	**2.00**	**86.46**	**3.24**	**3.04**
Heart and Vascular, Vascular, Catheters, Angioplasty, *Atherectomy*	**27.85**	**2.25**	**1.96**	**37.32**	**1.40**	**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	0.89	0.83
Orthopedics, Fixation, Screws	17.28	1.40	1.22	67.30	2.52	2.37
Optics, Intraocular, General, Lenses Intraocular	15.10	1.22	1.07	17.51	0.66	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	0.58	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	1.55	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	0.67	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	26.43	0.99	0.93
Heart and Vascular, Vascular, Catheters, Guiding, General, Catheters Vascular Guiding	8.09	0.65	0.57	10.84	0.41	0.38
Top 30 device categories	833.07	67.27	58.75	1,890.68	70.76	66.52

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 and TAVR; 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. For this reason, we exclude them from our main analysis and limit our focus to the remaining ten "important" device categories. These are bolded in Table A5, noting our preferred abbreviation for each category in italics. They account for 47 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, **ICDs**, **knees**, **hips**, **shoulders**, spinal **screws**, spinal **spacers**, and **SCS** implants.

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; Cardiology (excluding Interventional Cardiology) and Cardiac Electrophysiology (including Clinical) for ICD; Orthopedic Surgery for Hips, Knees, and Shoulders; Orthopedic Surgery and Neurosurgery for Screws and Spacers; and Pain Management (including Interventional), Neurosurgery, and Anesthesiology for SCS.

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	272.78
	(199.72)	(215.76)	(231.63)	(233.13)	(236.74)
Percent Medicare	50.04	48.40	47.52	46.44	46.58
	(13.84)	(11.99)	(12.65)	(11.79)	(10.75)
Percent Medicaid	18.31	19.50	20.77	21.32	21.15
	(10.84)	(10.69)	(11.35)	(11.19)	(10.44)
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	0.47
	(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)	(0.20)
Number of hospitals	4,492	3,235	1,117	999	933

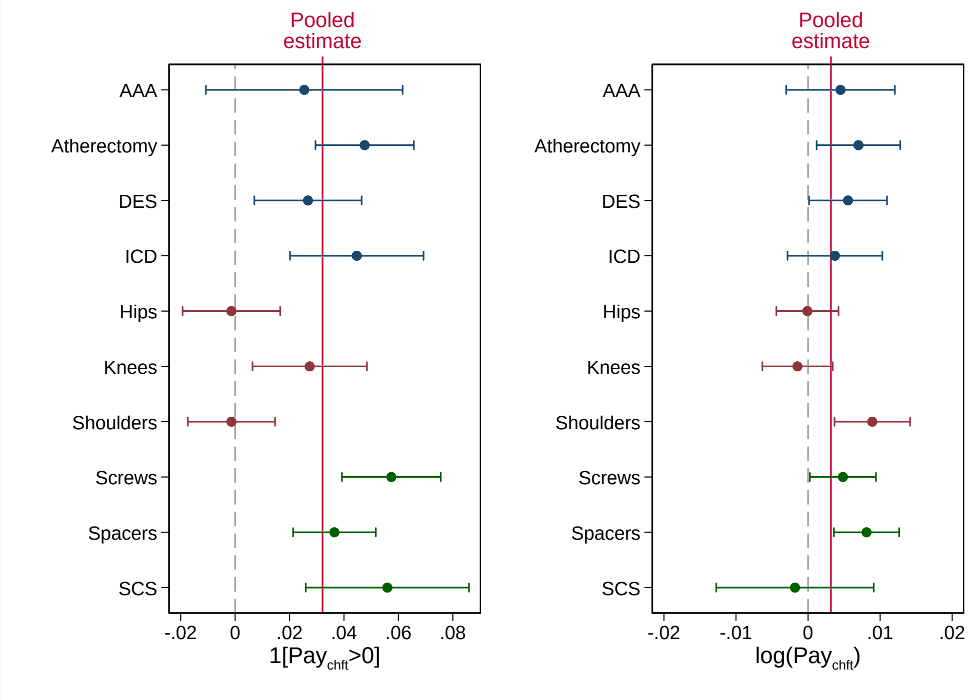
Notes: Open Payments columns summarize hospitals whose affiliated physicians received general, non-research, device-related payments during 2014-2017, before and after restricting to firms selling products in the focal device categories. Supply Guide columns summarize hospitals crosswalked from the Supply 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) ICD	(5) Hips	(6) Knees	(7) Shoulders	(8) Screws	(9) Spacers	(10) SCS
	Firm count	4	6	3	3	4	4	8	7	7	3
	Hospital count	472	696	619	618	891	885	824	746	692	616
	Hospital-period count	2,660	4,054	3,666	3,540	5,146	5,120	4,584	4,282	4,006	3,258
	Observations	10,640	24,324	10,998	10,620	20,584	20,480	36,672	29,974	28,042	9,774
	Physician Payments										
	Hospital-period payments ($1,000s)	2	2	2	3	11	19	6	15	8	1
		(10)	(6)	(11)	(31)	(65)	(144)	(59)	(82)	(35)	(8)
	Any hospital-period payments (%)	74	73	79	81	65	71	58	73	77	42
All	$1[Pay_{chft} > 0]$ (%)	39	26	52	54	28	33	13	27	30	21
All	$Pay_{chft} \| Pay_{chft} > 0$ ($)	469	66	68	80	925	1,326	406	575	245	56
		(1,835)	(658)	(422)	(804)	(6,679)	(14,388)	(3,929)	(6,532)	(1,848)	(840)
Meal	$1[Pay_{chft} > 0]$ (%)	39	25	50	53	26	31	11	24	28	21
Meal	$Pay_{chft} \| Pay_{chft} > 0$ ($)	107	11	14	21	15	25	9	11	8	10
		(159)	(22)	(22)	(33)	(30)	(41)	(32)	(24)	(14)	(14)
Educ	$1[Pay_{chft} > 0]$ (%)	9	8	16	17	14	15	6	11	12	2
Educ	$Pay_{chft} \| Pay_{chft} > 0$ ($)	667	51	66	89	116	157	61	68	46	69
		(2,266)	(368)	(322)	(1,296)	(255)	(375)	(175)	(167)	(108)	(152)
CHS	$1[Pay_{chft} > 0]$ (%)	4	3	7	7	5	5	3	5	5	1
CHS	$Pay_{chft} \| Pay_{chft} > 0$ ($)	1,878	315	236	166	845	1,274	371	517	355	310
		(2,756)	(1,584)	(927)	(264)	(1,717)	(2,524)	(1,146)	(890)	(792)	(382)
Own	$1[Pay_{chft} > 0]$ (%)	0.06	0.21	1	1	1	2	1	3	3	0.02
Own	$Pay_{chft} \| Pay_{chft} > 0$ ($)	6,084	86	231	552	13,561	19,266	4,690	3,837	1,654	26,203
		(14,104)	(214)	(674)	(2,388)	(24,785)	(57,988)	(14,189)	(18,737)	(5,550)	(1,349)
	Devices Purchases										
	Hospital-period sales ($1,000s)	290	75	359	577	299	438	98	396	235	163
		(350)	(122)	(363)	(671)	(413)	(588)	(155)	(602)	(321)	(214)
	$1[Sales_{chft} > 0]$ (%)	52	39	65	63	61	60	25	42	41	53
	$Sales_{chft} \| Sales_{chft} > 0$ ($)	30,916	1,174	11,222	16,852	12,359	19,177	1,960	5,287	3,411	6,962
		(72,157)	(4,673)	(20,231)	(49,809)	(33,879)	(59,783)	(10,518)	(18,376)	(10,775)	(23,614)
	$Price_{chft}$ ($)	5,946	2,293	1,246	16,506	1,454	1,620	2,107	482	3,466	12,783
		(2,219)	(1,089)	(176)	(3,102)	(797)	(859)	(938)	(248)	(1,551)	(6,268)
	Q_{cht}	21	3	28	3	39	59	8	74	8	2
		(27)	(5)	(29)	(6)	(68)	(113)	(19)	(103)	(11)	(4)
	$Q_{chft}/Q_{cht} \| Q_{chft} > 0$ (%)	44	38	47	48	38	38	45	31	32	54
		(33)	(30)	(32)	(32)	(34)	(34)	(36)	(31)	(31)	(34)
	Top firm share (%)	78	73	76	77	76	76	80	73	70	80
		(19)	(21)	(19)	(19)	(20)	(20)	(21)	(22)	(22)	(20)
	Other Hospital Characteristics										
	Num. of relevant physicians	3	14	13	14	7	7	7	10	11	11
		(2)	(12)	(11)	(12)	(6)	(6)	(6)	(8)	(8)	(8)
	Beds	416	352	365	363	293	293	309	333	343	353
		(264)	(248)	(252)	(257)	(246)	(247)	(251)	(251)	(253)	(239)
	% Medicare	45	45	45	45	46	46	46	46	46	45
		(10)	(10)	(9)	(10)	(10)	(10)	(10)	(10)	(9)	(9)
	% Medicaid	22	22	22	22	21	21	21	21	21	21
		(10)	(11)	(10)	(11)	(10)	(10)	(10)	(10)	(10)	(9)
	Nonprofit (%)	83	81	82	81	82	83	83	82	81	83
	Government (%)	13	12	12	13	11	11	11	11	11	11
	Teaching (%)	63	54	55	54	47	47	49	52	54	54
	Top AMC (%)	17	13	13	14	11	11	12	13	13	12

Notes: Device payments and purchasing statistics are from authors' calculations using Open Payments and Supply Guide data, respectively. The hospital-period payments variable is the average payment amount from all firms to all physicians at the category-hospital-period level, while the remaining payments rows are at the category-hospital-firm-period level. The hospital-period sales variable is the average value of sales from all firms to the hospital at the category-period level.

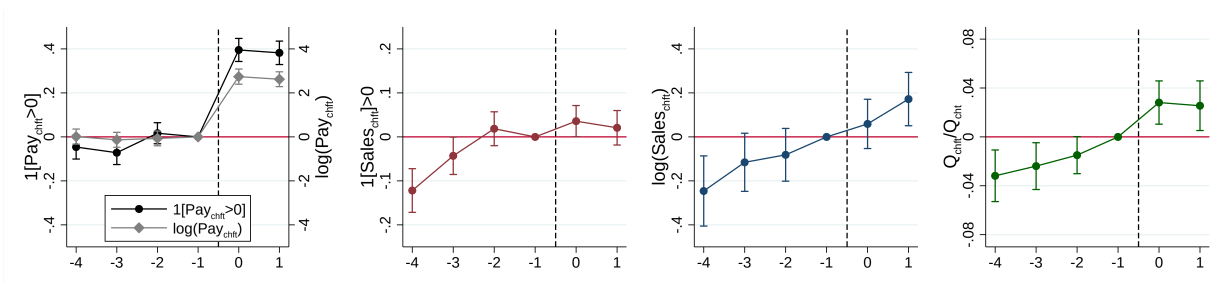
Figure A1: Association between Physician Payments and $1[Sale_{chft} > 0]$, by Device Category



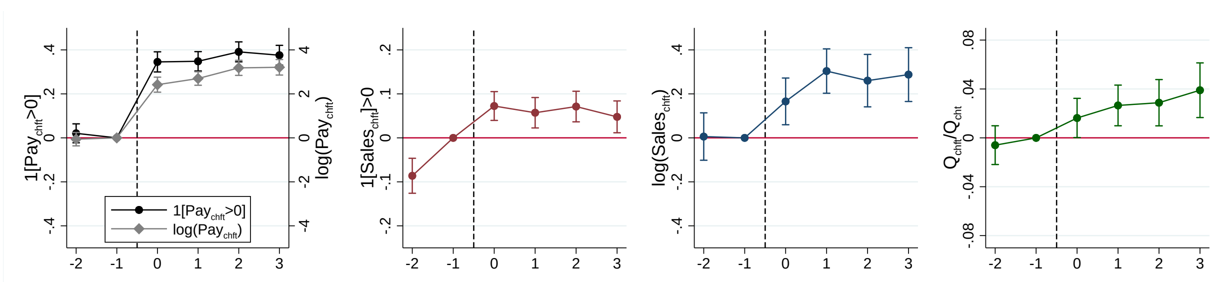
Notes: Authors' calculations using Open Payments and Supply Guide data. Category-specific extensive and intensive margin Pay_{chft} coefficient estimates, based on the model presented in equation (1), for the dependent variable $1[Sales_{chft} > 0]$, controlling for hospital controls (with category-varying 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 (2).

Figure A2: Event Study, by Event Analysis Window

(a) Two Years Pre, One Year Post



(b) One Year Pre, Two Years Post



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. In panel (a), the analysis sample includes 48 event hospitals, and 255 control hospitals, in the average category. This results in 70,412 observations total for dependent variable (d.v.) $1[Pay_{chft} > 0]$, 4,180 observations for d.v. $\log(Pay_{chft})$, 70,412 observations for d.v. $1[Sales_{chft} > 0]$, 21,447 observations for d.v. $\log(Sales_{chft})$, and 63,934 observations for d.v. Q_{chft}/Q_{cht}. In panel (b), the analysis sample includes 66 event hospitals, and 249 control hospitals, in the average category. This results in 70,078 observations total for d.v. $1[Pay_{chft} > 0]$, 5,325 observations for d.v. $\log(Pay_{chft})$, 70,078 observations for d.v. $1[Sales_{chft} > 0]$, 22,279 observations for d.v. $\log(Sales_{chft})$, and 63,741 observations for d.v. Q_{chft}/Q_{cht}.

Table A8: Summary Statistics: Regression Covariates

Variable	Mean	S.D.
Hospital-Category level		
log(Total Medicare billing)	13.834	1.330
log(Physician count)	1.874	0.940
log(Beneficiaries per physician-service)	7.303	0.855
log(Physician work RVU)	0.282	0.487
Hospital Level		
log(Full time physicians and dentists)	2.310	2.000
Share Medicaid discharges	0.214	0.102
Share Medicare discharges	0.457	0.098
Integrated salary model hospital	0.430	0.495

Notes: Sample average and standard deviation of the "baseline set" of regression controls described in 2.1, weighting each device category equally. Sample statistics from 21,518 observations identifying a (category, hospital, period) triplet.

Table A9: Regression Results – Full Sample vs. Payment Shocks

(a) Dep. Variable: $1[Sale_{chft} > 0]$

		Event Study Sample			
	Full Sample OLS	OLS	First Stage	Reduced Form	IV
$\log(Pay_{chft} + 1)$	0.010**	0.015**			0.036**
	(0.001)	(0.003)			(0.007)
$1[t \geq \tau_{chf}]$			2.604**	0.094**	
			(0.078)	(0.019)	
Observations	202,108	50,200	50,200	50,200	50,200
R-squared	0.657	0.672	-	0.672	0.002

(b) Dep. Variable: $\log(Sale_{chft})$

		Event Study Sample			
	Full Sample OLS	OLS	First Stage	Reduced Form	IV
$\log(Pay_{chft} + 1)$	0.027**	0.041**			0.100**
	(0.003)	(0.010)			(0.025)
$1[t \geq \tau_{chf}]$			2.660**	0.265**	
			(0.103)	(0.067)	
Observations	87,580	16,277	16,277	16,277	16,277
R-squared	0.802	0.788	-	0.788	0.006

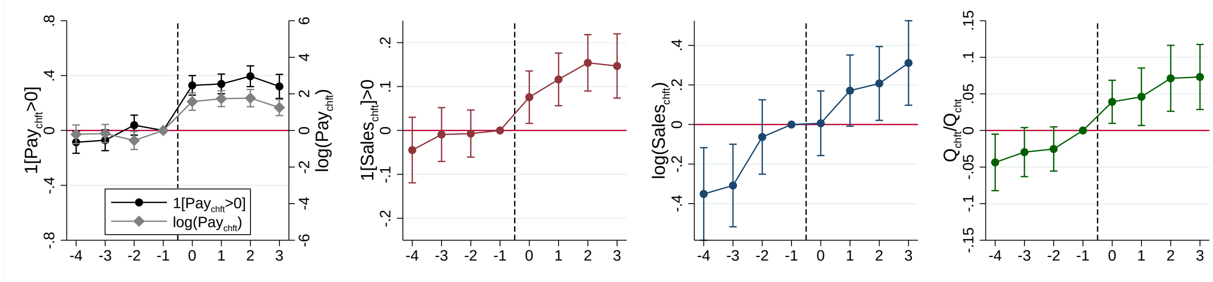
(c) Dep. Variable: Q_{chft}/Q_{cht}

		Event Study Sample			
	Full Sample OLS	OLS	First Stage	Reduced Form	IV
$\log(Pay_{chft} + 1)$	0.006**	0.007**			0.020**
	(0.000)	(0.002)			(0.005)
$1[t \geq \tau_{chf}]$			2.572**	0.052**	
			(0.081)	(0.012)	
Observations	178,659	47,265	47,265	47,265	47,265
R-squared	0.812	0.814	-	0.814	-0.001

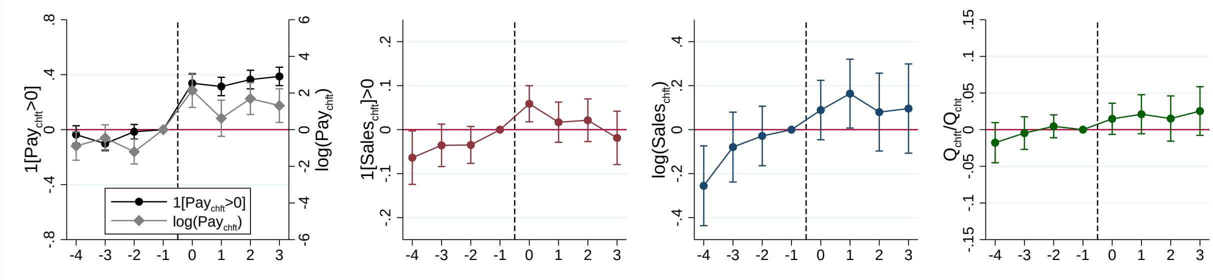
Notes: "Full sample OLS" regresses indicated device sales dependent variables (d.v.) on $\log(Pay_{chft} + 1)$, using the same regression sample as in Table 2; "OLS" regresses sales d.v. on $\log(Pay_{chft} + 1)$, limiting the sample to the event and control hospitals in Figure 2. "First Stage" and "Reduced Form" regress $\log(Pay_{chft}+1)$ and sales d.v., respectively, on a dummy for post-event periods. "IV" regresses sales d.v. on $\log(Pay_{chft} + 1)$, instrumenting with a dummy for post-event periods. All specifications control for all hospital and region characteristics, interacted with category dummies, category-hospital-firm fixed effects, and category-firm-period fixed effects. Standard errors clustered at the hospital-category level in parentheses. ** $p<0.01$, * $p<0.05$.

Figure A3: Event Study, by Nature of Payment

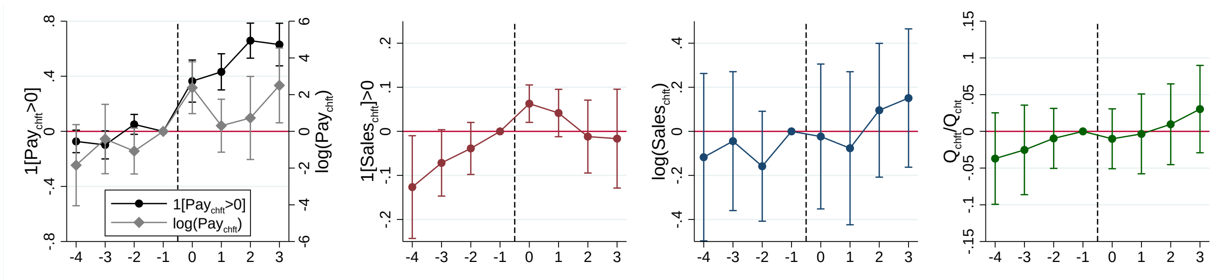
(a) Meal Payments



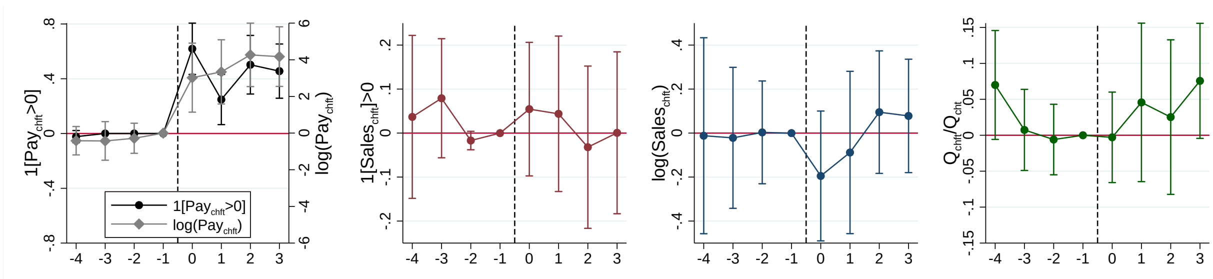
(b) Education and Travel Payments



(c) Consulting Fees, Honoraria, and Speaking Fees



(d) Royalty, Licensing, and Investment Payments



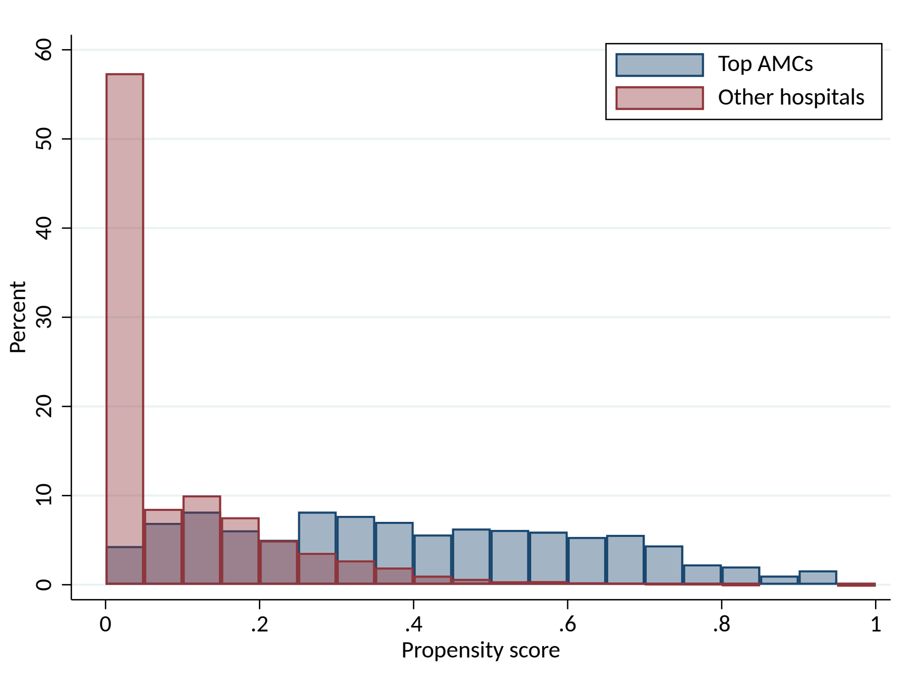
Notes: Authors' calculations using Open Payments and Supply Guide data. The x-axis denotes event time in periods, defined relative to the period of the hospital-category-specific payment shock. In panel (a), the analysis sample includes 21 event hospitals, and 178 control hospitals, in the average category. This results in 50,040 observations total for dependent variable (d.v.) $1[Pay_{chft} > 0]$, 3,056 observations for d.v. $\log(Pay_{chft})$, 50,040 observations for d.v. $1[Sales_{chft} > 0]$, 16,063 observations for d.v. $\log(Sales_{chft})$, and 47,131 observations for d.v. Q_{chft}/Q_{cht}. In panel (b), the analysis sample includes 23 event hospitals, and 242 control hospitals, in the average category. This results in 77,912 observations total for d.v. $1[Pay_{chft} > 0]$, 1,714 observations for d.v. $\log(Pay_{chft})$, 77,912 observations for d.v. $1[Sales_{chft} > 0]$, 32,325 observations for d.v. $\log(Sales_{chft})$, and 73,766 observations for d.v. Q_{chft}/Q_{cht}. In panel (c), the analysis sample includes 5 event hospitals, and 265 control hospitals, in the average category. This results in 103,112 observations total for d.v. $1[Pay_{chft} > 0]$, 655 observations for d.v. $\log(Pay_{chft})$, 103,112 observations for d.v. $1[Sales_{chft} > 0]$, 47,905 observations for d.v. $\log(Sales_{chft})$, and 97,912 observations for d.v. Q_{chft}/Q_{cht}. In panel (d), the analysis sample includes 2 event hospitals, and 272 control hospitals, in the average category. This results in 113,184 observations total for d.v. $1[Pay_{chft} > 0]$, 434 observations for d.v. $\log(Pay_{chft})$, 113,184 observations for d.v. $1[Sales_{chft} > 0]$, 55,408 observations for d.v. $\log(Sales_{chft})$, and 107,692 observations for d.v. Q_{chft}/Q_{cht}.

Table A10: Probit Regression Coefficients

	Category interaction term									
	AAA	Atherectomy	DES	ICD	Hips	Knees	Shoulders	Screws	Spacers	SCS
log(Num. of relevant physicians)	0.243**	0.528**	0.198**	0.295**	0.140**	0.153**	0.160**	0.165**	0.188**	0.310**
	(0.064)	(0.057)	(0.059)	(0.059)	(0.051)	(0.052)	(0.055)	(0.058)	(0.059)	(0.075)
log(Physician work RVU)	-0.054	0.068	-0.131	0.156	0.064	0.096	0.072	0.049	0.011	-0.118
	(0.073)	(0.101)	(0.130)	(0.116)	(0.067)	(0.068)	(0.073)	(0.082)	(0.088)	(0.108)
log(Physician beneficiary-days)	-0.300**	-0.380**	-0.605**	-0.328**	-0.507**	-0.498**	-0.563**	-0.515**	-0.550**	-0.609**
	(0.049)	(0.051)	(0.068)	(0.054)	(0.046)	(0.046)	(0.051)	(0.049)	(0.051)	(0.065)
% Medicare	-2.993**	-0.497	-1.260**	-0.592	-0.893*	-0.885*	-1.099**	-1.156**	-1.144**	-1.558**
	(0.524)	(0.472)	(0.480)	(0.496)	(0.395)	(0.397)	(0.407)	(0.429)	(0.440)	(0.519)
% Medicaid	-0.685	1.191**	-0.411	0.378	-0.778*	-0.710*	-0.892*	-0.425	-0.344	-0.045
	(0.410)	(0.348)	(0.378)	(0.372)	(0.347)	(0.354)	(0.371)	(0.374)	(0.390)	(0.458)
log(Beds)	0.226**	-0.001	0.165	0.087	0.277**	0.278**	0.230**	0.215**	0.233**	0.151
	(0.081)	(0.082)	(0.085)	(0.084)	(0.057)	(0.057)	(0.059)	(0.067)	(0.068)	(0.087)
Nonprofit	-1.310**	-0.766**	-0.518**	-0.243	-0.785**	-0.799**	-0.904**	-0.690**	-0.782**	-0.691**
	(0.181)	(0.142)	(0.151)	(0.179)	(0.133)	(0.134)	(0.144)	(0.143)	(0.143)	(0.174)
Government	-0.669**	0.094	0.003	0.597**	-0.225	-0.282	-0.313	-0.174	-0.271	-0.294
	(0.195)	(0.157)	(0.169)	(0.191)	(0.150)	(0.151)	(0.163)	(0.161)	(0.161)	(0.194)
Teaching	1.800**	1.991**	1.954**	5.306	1.946**	1.926**	1.966**	1.792**	1.743**	2.002**
	(0.193)	(0.246)	(0.229)	(114.032)	(0.160)	(0.161)	(0.167)	(0.163)	(0.163)	(0.260)
Intercept		-1.377	0.973	-5.159	-0.559	-0.659	0.279	-0.223	-0.014	0.387
		(0.951)	(1.023)	(114.036)	(0.867)	(0.867)	(0.882)	(0.890)	(0.898)	(0.985)

Notes: Coefficient estimates from a probit regression used to construct IPW used in estimating equation (3). Each variable (row) was interacted with a category indicator (column) to define a category-specific coefficient. Using 40,316 observations. Pseudo R-squared=0.355. Robust standard errors in parentheses. ** p<0.01, * p<0.05.

Figure A4: Propensity Score Distribution, by Expert Status



Notes: Propensity score prediction from a probit regression used to construct IPW used in estimating equation (3). Probit regression estimates are presented in A10.

Table A11: 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	94	73	70	612	559	365
Hospital-period count	555	272	283	3,477	2,417	1,060
Observations	2,067	1,003	1,064	13,013	9,064	3,949
Pay_{cht} (\$1,000s)	0.95	0.01	2.22	0.40	0.01	1.36
	(5.74)	(0.02)	(8.66)	(6.18)	(0.02)	(11.33)
$Sales_{cht}$ (\$1,000s)	37	33	44	38	34	47
	(69)	(64)	(74)	(87)	(86)	(89)
Num. of relevant physicians	11	8	16	9	8	12
	(10)	(8)	(12)	(9)	(6)	(11)
Physician work RVU	1.52	1.41	1.71	1.46	1.41	1.60
	(0.84)	(0.81)	(0.83)	(1.17)	(1.23)	(0.96)
Physician beneficiary-days	1,958	2,149	1,575	2,175	2,261	2,024
	(1,592)	(1,729)	(1,115)	(1,654)	(1,726)	(1,515)
% Medicare	44	46	42	46	46	45
	(10)	(10)	(9)	(9)	(9)	(9)
% Medicaid	21	20	22	21	22	21
	(11)	(11)	(10)	(9)	(9)	(9)
Beds	386	308	504	323	295	391
	(305)	(265)	(322)	(208)	(186)	(237)
Nonprofit (%)	86	88	81	71	67	79
Government (%)	12	9	16	9	9	11
Teaching (%)	100	100	100	45	39	59

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 A12: Optimal Device Mix Regressions: Coefficient Estimates

	Unweighted		IPW-Weighted		Matched Sample	
Coefficient	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
$1[Pay_{chft}]$	0.040**	0.007	0.058**	0.012	0.040**	0.012
$1[Pay_{chft} > 0] \times 1[NonTopAMC_h]$	0.020**	0.008	-0.008	0.012	0.016	0.015
$\log(Pay_{chft})$	0.019**	0.002	0.022**	0.003	0.021**	0.003
$\log(Pay_{chft}) \times 1[NonTopAMC_h]$	0.005*	0.002	0.001	0.003	0.007	0.004
$\eta_{AAA,1} \times 1[NonTopAMC_h]$	-0.091**	0.031	-0.083	0.043	-0.090*	0.038
$\eta_{AAA,2} \times 1[NonTopAMC_h]$	0.132**	0.024	0.113**	0.030	0.064*	0.031
$\eta_{AAA,3} \times 1[NonTopAMC_h]$	-0.052*	0.023	-0.011	0.027	-0.039	0.031
$\eta_{AAA,4} \times 1[NonTopAMC_h]$	-0.003	0.010	-0.003	0.012	-0.046**	0.017
$\eta_{Atherectomy,1} \times 1[NonTopAMC_h]$	-0.129**	0.031	-0.196**	0.066	-0.090*	0.039
$\eta_{Atherectomy,2} \times 1[NonTopAMC_h]$	0.042	0.025	0.171**	0.057	0.043	0.030
$\eta_{Atherectomy,3} \times 1[NonTopAMC_h]$	-0.032	0.021	0.028	0.023	-0.055	0.034
$\eta_{Atherectomy,4} \times 1[NonTopAMC_h]$	0.065**	0.019	0.023	0.036	0.016	0.031
$\eta_{DES,1} \times 1[NonTopAMC_h]$	-0.020	0.039	-0.219**	0.083	-0.037	0.061
$\eta_{DES,2} \times 1[NonTopAMC_h]$	-0.065	0.037	0.100	0.065	-0.060	0.048
$\eta_{DES,3} \times 1[NonTopAMC_h]$	0.028	0.030	0.129**	0.045	0.034	0.035
$\eta_{ICD,1} \times 1[NonTopAMC_h]$	-0.033	0.030	0.008	0.045	-0.034	0.043
$\eta_{ICD,2} \times 1[NonTopAMC_h]$	-0.018	0.027	-0.029	0.039	-0.041	0.043
$\eta_{ICD,3} \times 1[NonTopAMC_h]$	-0.013	0.016	0.034*	0.015	-0.009	0.020
$\eta_{Hips,1} \times 1[NonTopAMC_h]$	-0.128**	0.035	-0.113*	0.057	-0.156**	0.047
$\eta_{Hips,2} \times 1[NonTopAMC_h]$	0.070*	0.033	0.006	0.057	0.001	0.048
$\eta_{Hips,3} \times 1[NonTopAMC_h]$	0.038	0.034	0.086	0.062	0.054	0.046
$\eta_{Hips,4} \times 1[NonTopAMC_h]$	0.020	0.019	0.066**	0.019	0.044	0.027
$\eta_{Knees,1} \times 1[NonTopAMC_h]$	0.037	0.036	0.041	0.056	-0.057	0.048
$\eta_{Knees,2} \times 1[NonTopAMC_h]$	-0.010	0.034	0.048	0.059	0.034	0.043
$\eta_{Knees,3} \times 1[NonTopAMC_h]$	-0.078*	0.032	-0.089	0.055	-0.108**	0.040
$\eta_{Knees,4} \times 1[NonTopAMC_h]$	0.031	0.018	0.048*	0.024	0.044	0.026
$\eta_{Shoulders,1} \times 1[NonTopAMC_h]$	0.049	0.040	0.132**	0.046	0.071	0.051
$\eta_{Shoulders,2} \times 1[NonTopAMC_h]$	-0.048	0.031	0.004	0.051	-0.044	0.037
$\eta_{Shoulders,3} \times 1[NonTopAMC_h]$	-0.034	0.034	-0.089	0.048	-0.080	0.045
$\eta_{Shoulders,4} \times 1[NonTopAMC_h]$	-0.007	0.020	-0.012	0.026	-0.023	0.027
$\eta_{Screws,1} \times 1[NonTopAMC_h]$	-0.109**	0.032	-0.045	0.053	-0.160**	0.038
$\eta_{Screws,2} \times 1[NonTopAMC_h]$	0.051	0.029	0.039	0.046	-0.023	0.042
$\eta_{Screws,3} \times 1[NonTopAMC_h]$	0.030	0.019	0.016	0.035	0.053	0.027
$\eta_{Screws,4} \times 1[NonTopAMC_h]$	0.049**	0.015	0.061**	0.016	0.054	0.030
$\eta_{Spacers,1} \times 1[NonTopAMC_h]$	-0.070*	0.032	0.013	0.045	-0.130**	0.038
$\eta_{Spacers,2} \times 1[NonTopAMC_h]$	0.037	0.032	-0.001	0.066	0.015	0.041
$\eta_{Spacers,3} \times 1[NonTopAMC_h]$	-0.017	0.025	0.024	0.051	-0.026	0.029
$\eta_{Spacers,4} \times 1[NonTopAMC_h]$	0.029	0.025	0.023	0.031	0.058	0.034
$\eta_{SCS,1} \times 1[NonTopAMC_h]$	-0.019	0.036	0.104	0.065	-0.067	0.041
$\eta_{SCS,2} \times 1[NonTopAMC_h]$	0.028	0.028	0.025	0.035	0.026	0.034
$\eta_{SCS,3} \times 1[NonTopAMC_h]$	-0.037	0.031	-0.108*	0.051	0.005	0.038
R-squared	0.213		0.260		0.258	
Observations	135,857		135,857		33,759	

Notes: Estimation results of the model presented in equation (3), absorbing category-firm-period fixed effects. Standard errors clustered by hospital-category in parentheses. ** $p<0.01$, * $p<0.05$.

Table A13: Association between Market Share, Top AMC Status, and Payments by Device Category

(a) Regression Estimates

	(1) AAA	(2) Atherectomy	(3) DES	(4) ICD	(5) Hips	(6) Knees	(7) Shoulders	(8) Screws	(9) Spacers	(10) SCS
$1[Firm\#1] \times 1[NonTopAMC_h]$	-0.106*	-0.190**	-0.148	-0.00619	-0.0989	0.0662	0.120*	-0.0572	0.00314	0.110
	(0.0455)	(0.0582)	(0.0825)	(0.0440)	(0.0545)	(0.0568)	(0.0510)	(0.0540)	(0.0478)	(0.0696)
$1[Firm\#2] \times 1[NonTopAMC_h]$	0.103**	0.158**	0.106	-0.00919	0.00231	0.0786	0.0105	0.00708	-0.0161	0.00927
	(0.0303)	(0.0610)	(0.0696)	(0.0404)	(0.0591)	(0.0560)	(0.0523)	(0.0455)	(0.0637)	(0.0322)
$1[Firm\#3] \times 1[NonTopAMC_h]$	-0.0196	0.00820	0.121**	0.0204	0.106*	-0.0741	-0.0937	0.0128	0.0388	-0.132*
	(0.0275)	(0.0211)	(0.0431)	(0.0184)	(0.0524)	(0.0507)	(0.0494)	(0.0305)	(0.0514)	(0.0519)
$1[Firm\#4] \times 1[NonTopAMC_h]$	-0.0143	0.0280			0.0676**	0.0567**	-0.0150	0.0480**	0.0198	
	(0.00989)	(0.0278)			(0.0205)	(0.0215)	(0.0278)	(0.0181)	(0.0293)	
$1[Pay_{chft} > 0]$	0.0191	0.0331	0.151**	0.0465	0.0922*	0.0523	0.0794*	0.0428*	0.0310	0.0548
	(0.0246)	(0.0208)	(0.0338)	(0.0237)	(0.0447)	(0.0382)	(0.0403)	(0.0217)	(0.0288)	(0.0420)
$1[Pay_{chft} > 0] \times 1[NonTopAMC_h]$	-0.0456	0.0215	-0.0543	0.0130	-0.0377	-0.0537	-0.0101	0.00193	0.0107	0.00294
	(0.0284)	(0.0211)	(0.0337)	(0.0252)	(0.0473)	(0.0468)	(0.0442)	(0.0255)	(0.0363)	(0.0447)
$\log(Pay_{chft})$	0.0123*	0.0229**	0.0181	0.0304**	0.0234**	0.0299**	0.0154	0.0179**	0.0292**	0.00617
	(0.00488)	(0.00504)	(0.00967)	(0.00807)	(0.00717)	(0.00875)	(0.0104)	(0.00539)	(0.00756)	(0.0115)
$\log(Pay_{chft}) \times 1[NonTopAMC_h]$	0.0168**	-0.00283	-0.00393	-0.00818	0.00295	-0.000934	0.00437	0.00993	0.00236	0.0152
	(0.00600)	(0.00761)	(0.0107)	(0.00859)	(0.00877)	(0.00933)	(0.0110)	(0.00636)	(0.00869)	(0.0139)
Firm-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,764	14,556	10,077	9,573	18,840	18,716	16,112	15,412	14,452	8,355
R-squared	0.521	0.213	0.239	0.404	0.179	0.164	0.117	0.150	0.094	0.249

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

	(1) AAA	(2) Atherectomy	(3) DES	(4) ICD	(5) Hips	(6) Knees	(7) Shoulders	(8) Screws	(9) Spacers	(10) SCS
Top AMCs, Low/Zero Pay	0.041**	0.036**	0.093**	0.071**	0.076**	0.095**	0.033*	0.036**	0.033**	0.017
	(0.009)	(0.009)	(0.018)	(0.014)	(0.024)	(0.020)	(0.014)	(0.009)	(0.009)	(0.011)
Top AMCs, High Pay	0.137**	0.159**	0.326**	0.241**	0.297**	0.311**	0.182**	0.194**	0.236**	0.092
	(0.025)	(0.032)	(0.060)	(0.042)	(0.050)	(0.047)	(0.053)	(0.035)	(0.036)	(0.049)
Other Hospitals, Low/Zero Pay	0.159**	0.257**	0.239*	0.092**	0.186**	0.169**	0.162**	0.105**	0.079*	0.176*
	(0.041)	(0.070)	(0.093)	(0.014)	(0.052)	(0.049)	(0.046)	(0.029)	(0.035)	(0.078)
Other Hospitals, High Pay	0.221**	0.316**	0.352**	0.216**	0.318**	0.282**	0.229**	0.255**	0.261**	0.221**
	(0.026)	(0.054)	(0.073)	(0.024)	(0.037)	(0.036)	(0.038)	(0.025)	(0.028)	(0.065)

Notes: Panel (a), each column represents a device category-specific OLS regression based on the model presented in equation 3 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 3 with category-interacted coefficients. Standard errors calculated using the delta method in parentheses. ** p<0.01, * p<0.05.