Transparency and Negotiated Prices: The Value of Information in Hospital-Supplier Bargaining

PRELIMINARY AND INCOMPLETE – PLEASE DO NOT CITE OR CIRCULATE

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January 9, 2015

Abstract

This paper empirically analyzes the role of information in bargaining between hospitals and their suppliers. Hospital supplies account for a large percentage of both the level and growth of health care expenditures, and prices for the same input can vary dramatically across hospitals. This variation has prompted calls for increased transparency as a mechanism to lower prices, but whether such an intervention would be successful depends on the details of what information is provided and how market participants respond. We analyze a new data set including all purchase orders issued by over ten percent of US hospitals over 2009-13. The empirical setting contains an intervention in which sample hospitals gained access to benchmarking data on other hospitals' negotiated prices. Using differences-in-differences identification strategies based on timing of hospitals' access to price information and on new product entry, we find that access to information on purchasing by peer hospitals led to reductions in prices of up to four percent, which is similar to the estimated effect of forcing high priced hospitals' negotiated prices down to the mean. The heterogeneity in results suggests that price information is most effective among hospitals learning that they were performing relatively poorly in contracting and for hospitals' most preferred products, and that the usefulness of price information is constrained by delays in renegotiation between hospitals and suppliers.

*This paper benefited from comments from audiences at the 2015 ASSA meetings, University of California-Berkeley, iHEA 2014, the Indian School of Business, the University of Louisville, the Triangle Health Economics Workshop, and the Wharton IO Brownbag. We gratefully acknowledge financial support from the Wharton Dean's Research Fund and Public Policy Initiative. Biruk Bekele, Chetna Johry, and Jake Lahr provided excellent research assistance. Any errors are our own.

1 Introduction

Suppliers in business-to-business markets often negotiate different contracts with different buyers, and a buyer typically has limited information regarding other buyers' contracts. As technology has made data easier to collect, distribute, and analyze, many such markets have seen the entry of information intermediaries who facilitate buyers' ability to benchmark the prices they negotiate. Intuition suggests this information would be valuable to buyers in markets with imperfect or asymmetric information regarding product quality or costs. However, the implications of this type of increased transparency are not obvious—theoretically or empirically—in a market where both buyers and suppliers have market power and prices are negotiated. In this paper, we use a new data set on all purchase orders issued by ten percent of US hospitals from 2009-13 to estimate the impact of access to benchmarking information on the prices hospitals negotiate with their suppliers.

We have two primary goals in this study: (1) to estimate the treatment effect of transparency in negotiated prices, where transparency takes the form of benchmarking information on hospital supply prices; and (2) to inform theory development on the role of this type of transparency in negotiated price markets. Hospital supplies and devices are a particularly important area for this analysis as they have accounted for 24 percent of the dramatic growth in inpatient hospital costs between 2001 and 2006 (Maeda, et al. 2012), and policymakers have argued that improvements in hospital-supplier contracting may hold great potential for reducing health care system cost growth.[1] Indeed, across a broad set of product categories, there is substantial variation in prices across hospitals – for the top fifty hospital supplies by expenditure in our data, the average standard deviation of prices across hospitals for the same exact product and month is ten percent of the mean price. Recent legislation has proposed that the variation in prices across hospitals is at least in part due to a lack of transparency in these input markets, and further that increasing transparency would lower average prices.[2] The policy attention given to these prices reflects both a concern for the financial viability of hospitals and also a concern that rising supply costs over time filter downstream into higher costs for the health system and consumers.

To our knowledge, there is no economic model that incorporates the primary ways in which a benchmarking information intervention would be expected to affect price negotiations in a business-to-business market. Because buyers negotiate directly with a product's manufacturer, any impact of information on the prices other buyers are paying for a product must enter through this negotiation (in contrast with the more well-studied case of price-taking consumers shopping among multiple retailers offering different prices for the same item). Based on conversations with market participants, the most promising candidate mechanisms in our context are:

[1] For example, the recent Acute Care Episode demonstration, a bundled payment pilot orchestrated by the Centers for Medicare and Medicaid Services, found that lower costs at demonstration sites were achieved largely due to improved contracting with suppliers. *See* Calsyn and Emanuel (2014) for a discussion.

[2] For example, Senator Angus King of Maine recently added an amendment to a tax bill that would increase price transparency for medical devices, stating that "To the extent that prices of implantable medical devices . . . are not disclosed, the ability of hospitals to bring price information to bear in negotiations and decisions is clearly limited." ("King Calls," 2014)

(1) a model in which hospitals face uncertainty about suppliers' costs or bargaining parameters, so that price transparency reduces the degree of uncertainty and the equilibrium dispersion in negotiated prices; and (2) an agency model in which price transparency allows managers to better observe purchasing managers' effort and, in turn, provide improved incentives to purchasing managers to reduce prices.[3] While explicitly developing these theories is left for future research, our analysis does provide suggestive evidence for theory development in the sense that we provide a series of reduced-form facts that an appropriate theory must rationalize.

Our analysis is based on data from a large hospital supply benchmarking service, covering all purchase orders issued by ten percent of US hospitals between 2009 and 2013. In order to control for a host of differences across product categories, we focus our analysis on price negotiations for coronary stents and thus limit our sample to the 386 hospitals with cardiac catheterization service. Stents are a desirable category because they are important (one of the largest categories, comprising two percent of supply spend), typically have simple linear contracts (so the price observed on the purchase order is the price paid), and are physician preference items where doctor usage decisions are insensitive to price (making negotiating lower prices the main mechanism via which a hospital can obtain savings). The database is generated by monthly submissions from the member hospitals on prices and quantities of each item purchased, at the manufacturer stock-keeping-unit (SKU) level. Importantly, new member hospitals joining the database are asked to submit 12 months of retrospective data, so for any hospital joining during our sample period (about one third of the hospitals in the data) we observe data in pre- and post-information states.

Because different hospitals join at different times, we can construct differences-in-differences estimators based on the prices negotiated by hospitals with and without access to the benchmarking information, controlling for time-invariant differences in hospital-product prices and secular price trends. The assumption underlying this approach is that timing of join is uncorrelated with latent hospital-specific price trends. In particular, this strategy would fail if hospitals join when they are experiencing increases in input prices, or when they are enacting other cost-cutting measures beyond benchmarking. To provide reassurance on this point, we also perform additional analyses focusing only on new products entering the market during 2009-2013: because no information on others' prices is available when a new product first enters the market, this provides exogenous variation in the timing of information availability.

Measurement of the average treatment effect (ATE) of access to benchmarking information is complicated by a number of frictions that push the short-run effect for a product-hospital pair toward zero. Once a hospital joins the database, someone at the hospital must anticipate sufficient potential gains for a product to search the database for information regarding what other hospitals are paying. The information found must then be useful in the sense that it suggests the hospital has an opportunity to negotiate a better price. Finally, the hospital must

[3]To be more precise, the first mechanism is bargaining with one-sided incomplete information, on which there are many theory models. To our knowledge, there are no theory models that incorporate information on other buyers prices into a model with multilateral bargaining and oligopoly suppliers, as is typical in business-to-business markets; or that incorporate the second mechanism of negotiator agency.

engage the supplier to negotiate a new contract (the term of the existing contract may not expire for up to a year or more). To the extent that each of these potential frictions have substantive costs in terms of time or resources, a treatment effect measured based on the first step of having access to the benchmarking data will be biased toward zero. For this reason, we take this base treatment effect as a lower bound, and we construct an upper bound treatment effect by further conditioning on the next observed price change for each product-hospital pair, ensuring that the final step of negotiating a new contract has been reached.

The estimated lower bound ATE across product-hospital-months for coronary stents suggests that simply having access to the information in the database results in zero savings. The upper bound ATE, however, is over four percent ($50 per stent, where the average hospital uses over 800 stents per year), or 25 percent of the potential savings possible if every hospital were to pay the minimum price observed for each product in each month. This difference between the upper and lower bounds suggests that there are substantial frictions between having access to the benchmarking information and getting to the negotiating table where that information might be used to obtain a better price. When we focus our analysis on entering products (to alleviate concerns about endogeneity regarding the timing of hospitals joining the database), results are qualitatively similar but slightly larger in magnitude. The lower bound estimate suggests $20 in savings achieved per stent simply by joining the database; the upper bound estimate suggests $68 in savings achieved per stent at the first renegotiation after joining the database.

In order to better understand the intermediate frictions of the expected value of searching the database and of the usefulness of the information found from such a search, we use triple-differences models to estimate conditional average treatment effects for hospitals' most frequently used products and for products where the hospital is paying a high price relative to other hospitals. If there are any costs to searching for information in the database or to renegotiating with suppliers, then we would expect search and/or renegotiation efforts (and thus treatment effects) to be concentrated among products that the hospital uses more frequently. Similarly, both the model where hospitals have uncertain beliefs about supplier parameters and also the model of purchasing manager agency suggest that the value of the price information found after searching the database would be greater when the hospital is paying a higher price relative to other hospitals for a product.

Consistent with the above hypotheses, we find that both upper and lower bound treatment effects for a given hospital's most preferred product prior to accessing the benchmarking database are $20-$30 larger in magnitude than the ATEs for all other products. We also find that treatment effects are largest for those products for which the hospital is paying more relative to others – when hospitals gain access to the database, we estimate that additional savings per stent of $32 (at the lower bound) to $77 (at the upper bound) are achieved for products where the hospital is above the 75th percentile in the price distribution, relative to the ATE for the rest of the price distribution. Interestingly, in addition to this downward pinch at the top of the price distribution, we also find a negative shift in the entire distribution – even for

hospitals below the 25th percentile in the price distribution, the upper bound treatment effect is $24 in savings relative to uninformed hospitals. We consider this shift as suggestive evidence for the negotiator agency theory, as it is not clear how uncertainty about supplier parameters would lead to gains by hospitals who are already paying lower than average prices.

1.1 Related Literature, Public Policy, and Roadmap

Theory of how benchmarking information matters in business-to-business markets where prices are negotiated may differ from that where price-taking consumers search among retail outlets, but both relate to the broader question of the role of informed buyers on market outcomes. Much of the prior literature has measured how information affects search and outcomes such as price (Sorenson 2000) and quality (Jin and Leslie 2003; Bronnenberg et al. 2014), generally finding that demand side effects of information are on average null or beneficial to buyers. Our findings extend to negotiated prices and to models of bargaining under uncertainty and negotiator effort as explanations for how information can matter for buyers.

Our study also relates to the literature on supply side responses to transparency. In this literature, supply side responses can negate or overturn welfare-positive demand-side effects of transparency due to greater obfuscation (Ellison and Ellison 2009), facilitating collusion (Albek et al. 1997), or forcing coordination not to price discriminate via secret discounts (Grennan 2013). Our research design and the variation in the data will not allow us to estimate the first two. However, to the extent that suppliers know when buyers join our benchmarking database (and anecdotal evidence suggests that they do), then our estimates will incorporate the net effects of both informed buyers and also the potential reluctance of suppliers to cut any individual buyer a deal when that information will become part of other buyers' future information set. This makes our estimates more useful for considering the policy proposals that have put forth imposing greater transparency (in the most recent proposal through requiring quarterly reporting of average, minimum, and maximum prices) as a way to decrease prices for medical inputs.

Finally, the finding of a meaningful role of information on negotiated prices suggests an important future direction for the empirical bargaining literature (Crawford and Yurukoglu 2012; Grennan 2013; Gowrisankaran, Nevo, and Town 2014; Ho and Lee 2014), which has thus far modeled negotiations of perfect information. The evidence suggesting negotiator agency as a factor also points to effort as an endogenous determinant of bargaining ability parameters, which to our knowledge has not been modeled theoretically.

The paper proceeds by first examining the data, setting, and research design in Section 2. Section 3 discusses potential theoretical mechanisms for how benchmarking data might affect negotiated prices, based on existing theory and claims of industry participants. Section 4 presents our empirical results on the overall ATEs that are relevant for policy and cuts of the data designed to better understand mechanisms that inform future theory development. Section 5 concludes.

2 Data, Setting, and Research Design

2.1 Hospital Purchase Order Data

In order to investigate this research question, we have transaction data on all supply purchases made by about 10% of US hospitals during the period 2009-2013. This includes a wide range of products, encompassing commodities such as cotton swabs and gloves as well as physician preference items such as stents and orthopedic implants. There are 1.9m distinct products in almost 3,000 product categories in the data, which are reported monthly. For each transaction, we observe price, quantity (with relevant units), expenditure, transaction date, product (SKU and Universal Medical Devices Nomenclature System (UMDNS) code),[4] and supplier. We do not observe decrypted hospital information, but we observe unique identifiers for each member and the data include several coarse member characteristics: census region, facility type, and number of beds. Table 1 displays some summary statistics regarding the transactions data. We observe transactions for 1,384 members, 652 of which are hospitals. On average, we observe 25 months of transactions for members, 30 for hospitals. We observe purchases in more product categories for hospitals than for all members on average (754 vs. 441). The average hospital in our database spends $2.2 million per month on all supplies, $52 thousand of which is dedicated to coronary stents. As expected, hospitals generate the majority of the spending on stents – 60% of hospitals purchased stents during 2009-2013, vs. 33% across all members.

Table 1: Summary Statistics from Purchase Order Database

	All Members [N=1,384]		Hospitals [N=652]	
	Mean	SD	Mean	SD
Months of Data	24.74	14.83	29.30	14.16
Product Categories	441.38	434.61	754.35	339.77
Total Spend/Month ($m)	1.36	2.57	2.20	2.73
Purchases Stents?	0.33	0.47	0.59	0.49
Total Spend/Month on Stents ($k)	30.31	69.15	52.33	81.35

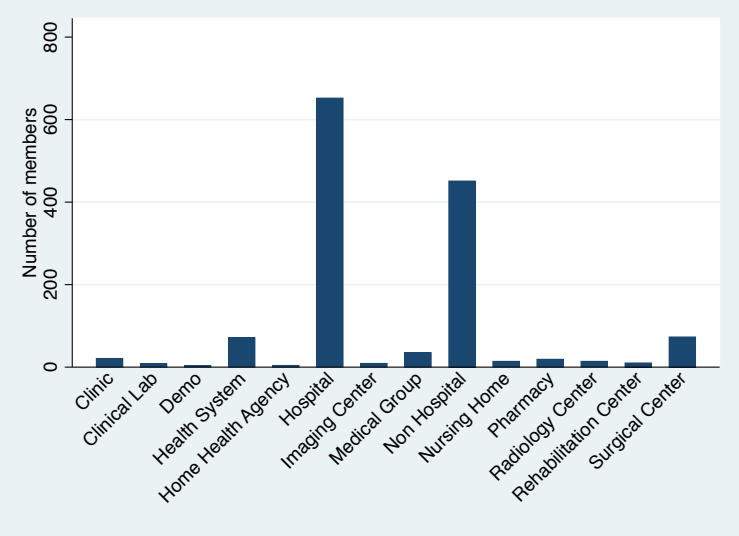
Notes: Summary statistics for all members in purchase order database, with hospital members broken out separately. Count of "Product Categories" based on UMDNS code in transaction record.

The data include multiple different types of facilities, such as hospitals, nursing homes, and surgical centers. See Figure 1 for the distribution of member types. The vast majority of members are hospitals, but there is also a large mass of members coded as "Non Hospital" or "Surgical Center." In this analysis, we restrict the sample to focus on the 386 hospitals we observe to purchase stents.

The sample hospitals in the purchase order data voluntarily joined a subscription service that allows them to benchmark purchasing by comparing their own prices and quantities to those of other hospitals in the database. The sample of hospitals joining the database is likely

[4] UMDNS is a standard international coding system for medical devices developed by the ECRI Institute.

Figure 1: Facility Types in Purchase Order Database



nonrandom. In particular, subscription is costly, so we expect hospitals with greater concerns about supply costs to be overrepresented in the database. Indeed, the sample is not perfectly representative of US hospitals with catheterization labs. The left panel of Figure 2 compares the distribution of sample hospitals across US census regions to that of Medicare-certified hospitals with cardiac catheterization labs.[5] The Figure shows that the west region is overrepresented in the sample data, while the south is underrepresented. We also note that the average sample hospital is larger than the average US hospital with cardiac catheterization capabilities – the right panel of Figure 2 shows that the sample contains disproportionately fewer hospitals in the < 300 beds range and disproportionately more hospitals in the ≥ 300 beds range, relative to Medicare hospitals that would purchase stents. This may be due to small hospitals' limited ability to afford access to the database, though we would expect a countervailing effect to come from large hospitals' ability to purchase custom benchmarking services from consulting firms. In our Results and Conclusions, we will discuss this issue of nonrepresentativeness.

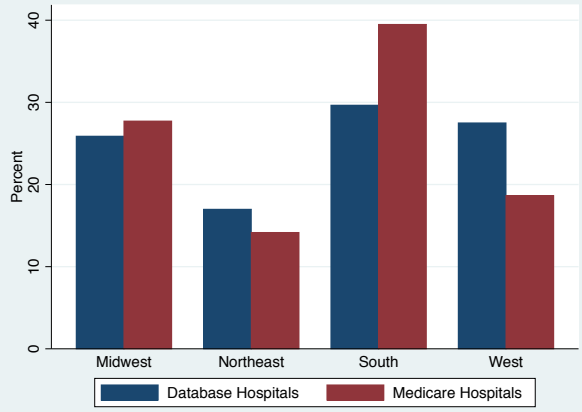
2.2 Coronary stents

As noted above, we focus on coronary stents in our empirical analysis. Coronary stents are small metal tubes placed into narrowed coronary arteries to widen them and allow blood flow to the heart. The original technology, the bare metal stent (BMS), was approved in the early 1990s; in the early 2000s, the drug-eluting stent (DES) was introduced as an improvement over

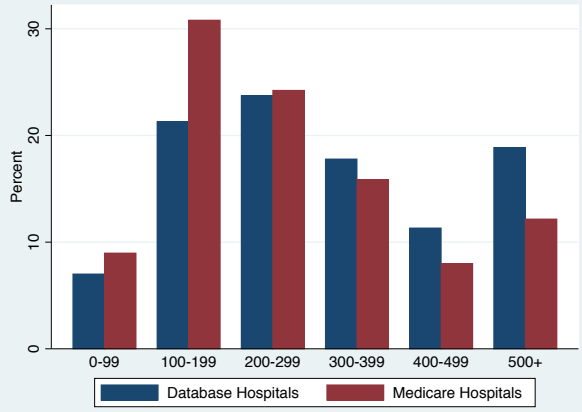
[5]Medicare comparison hospitals obtained by merging data from the Centers for Medicare and Medicaid Services' (CMS) Hospital Compare database from July 2013 with CMS's Healthcare Cost Report Information System (HCRIS) Indirect Medical Education (IME) data for fiscal year 2013. The Hospital Compare files contain data on hospital volume by diagnosis related group (DRG), including DRGs with the description "with cardiac cath" and/or "stent" – this file was used to identify hospitals with cardiac catheterization labs. The IME file contains data on hospital location and total bed capacity.

Figure 2: Distribution of Benchmarking Database vs. Medicare Hospitals

(a) Across Census Regions



(b) By Bed Size



the older technology with lower risk of restenosis, a condition that may arise when scar tissue builds up around the stent and restricts blood flow yet again.

Stents are an important product category, both in terms of overall sales and also as a percentage of hospital supply costs. In the US, hospitals spend more than two billion dollars annually on stents used in over 700,000 procedures[6]; in our transactions data, stents comprised two percent of overall supply costs among all members. Table 2 summarizes the stent transactions data for the restricted sample. The average sample hospital submitted stent transactions in 27 months. In a given month, sample hospitals spent $96,000 on 67 stents, 74% of which were drug-eluting (as opposed to bare metal) stents. The Table shows each statistic separately by hospital bed count; larger hospitals generally submitted more months' data and, as logic would indicate, purchased more stents per month for a greater total monthly expenditure. Hospitals with $\geq$ 500 beds spent more than triple the amount that the smallest hospitals did on stents per month.

Prices for stents have fallen substantially over time as products have proliferated; during 2009-Q2 2013, we observe data for eighteen branded products sold by four manufacturers – Abbott, Cordis, Medtronic, and Boston Scientific. Between Q1 2009 and Q2 2013, average prices decreased by 24 percent. Price differences across hospitals are substantial. In Figure 3, we show the distribution of prices across hospitals for bare metal and drug eluting stents. The Figure displays the distribution of hospital fixed effects, which were obtained from a regression of prices on dummies for hospitals, products, and months; that is, we show here the distribution of prices within product and month, so that price variation is not driven by differences in timing or composition of purchase. As we see in the Figure, drug-eluting stents are far more expensive than bare metal stents ($1,633 vs. $752), and there is substantial dispersion in prices across

[6] 700,000 estimate from Waldman, et al. (2013), referencing stent procedures in Medicare enrollee population. Two billion dollar figure based on authors' calculations using Boston Scientific's reported US revenue in 2012 (BSX 10-K 2012) and Boston Scientific's 2012 market share in purchase order data.

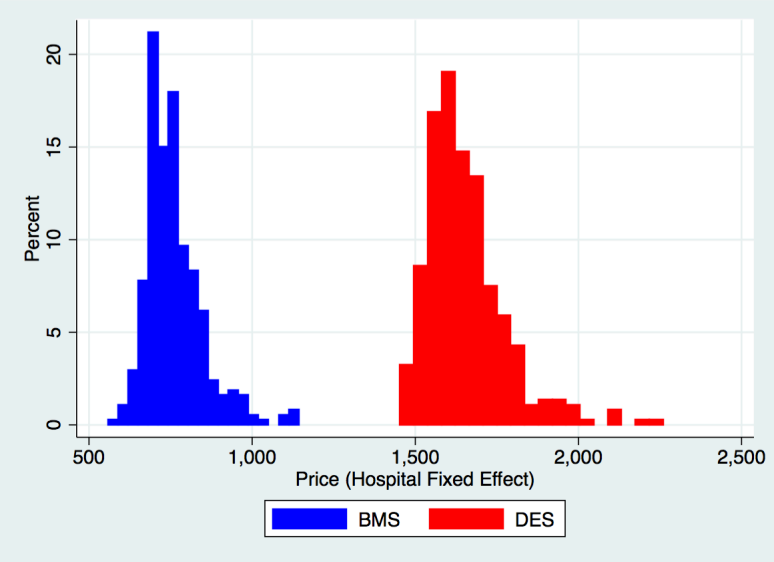
Table 2: Summary Statistics – Stent Hospitals Only

Bed Count	Members	Months	Monthly Expenditure ($k)	Monthly Quantity	% DES
0-99	26	21.2	50.0	35.5	76.5
		(16.7)	(48.1)	(33.6)	(21.0)
100-199	79	23.9	49.7	34.7	70.9
		(14.8)	(53.7)	(34.6)	(24.0)
200-299	88	30.1	69.7	48.7	73.5
		(14.4)	(66.3)	(46.4)	(19.5)
300-399	66	27.5	87.9	61.6	74.8
		(14.2)	(56.1)	(39.2)	(19.7)
400-499	42	29.6	140.6	97.8	74.2
		(14.9)	(102.4)	(69.8)	(16.4)
500+	70	29.0	172.8	121.9	78.0
		(13.6)	(203.2)	(152.1)	(12.9)

Notes: Summary statistics regarding stent transactions for hospitals in purchase order data. Sample restricted to hospitals with any stent transactions. Standard deviations in parentheses. "% DES" indicates percentage of members' coronary stent purchases devoted to drug-eluting (rather than bare metal) stents.

hospitals within each category. The interquartile range of prices across hospitals is $101 for bare metal stents, $139 for drug-eluting stents. If all prices were brought down to the minimum price within each product category, hospitals would save 12-27% on average; if, instead, all hospital prices above the mean price within each product category were brought down to the mean, hospitals would save 2.4-3.6% on average.

Figure 3: Distribution of Prices Across Hospitals

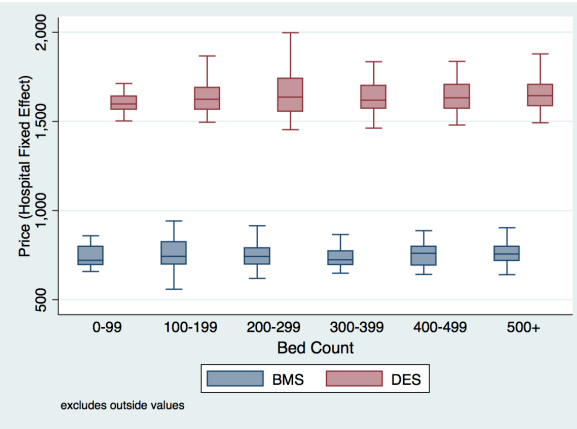


Interestingly, we are unable to associate much of this observed price dispersion with hospital characteristics that would seem a priori to be important for negotiation. For example, in spite

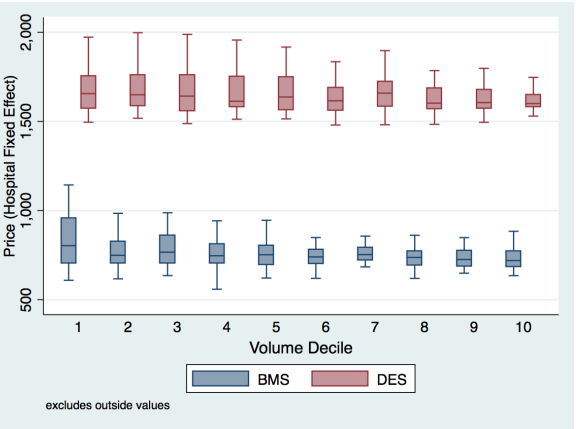
of the fact that the largest hospitals spend triple the dollar amount on stent purchases as the smallest hospitals do, we observe no clear relationship between hospital size and stent prices. See Figure 4, in which we display a box plot of bare metal and drug-eluting stent prices for each category of bed count.[7] The price distributions are, if anything, increasing in bed count, though the differences are not statistically significant. Part of this (lack of) relationship is likely due to the heterogeneity in purchasing behavior across hospitals with similar bed counts – small cardiac specialty hospitals purchase stents in greater quantities than similarly-sized acute care hospitals. We cannot directly observe measures of hospital specialization; however, we do observe purchase volume. In Figure 4, we also show box plots of stent prices for each decile of stent purchasing volume. Here, we do see a relationship between "size" and price – the hospitals with the smallest purchasing volumes have price distributions which are spread slightly upward relative to that of the hospitals with the largest volumes, so that low-volume hospitals' prices have larger means and variances than high-volume hospitals. For bare metal stents, 10^{th} decile hospitals' prices are 13% lower than those obtained by 1^{st} decile hospitals; the equivalent comparison figure for drug-eluting stents is 6%. These differences are economically and statistically significant; however, the price distributions for the high-volume and low-volume hospitals overlap substantially, so that there is a great deal of unexplained hospital price heterogeneity conditional on purchasing volume.

Figure 4: Distribution of Prices Across Hospitals

(a) By Bed Count



(b) By Stent Volume Decile



One potential explanation for this residual heterogeneity may be that stents are "physician preference items," products whose demand is determined in large part by physician preferences and which are particularly prominent targets for cost savings by hospital administrators. Policymakers have long argued that the primacy of physician preference in determining demand for such products has limited hospitals' ability to constrain costs using negotiating tools such as standardization. In the following Section, we discuss the potential role of cooperation be-

[7] As before, "prices" are hospital fixed effects obtained from a regression of price on hospital, month, and product fixed effects.

tween physicians and hospitals in determining prices. It is worth noting here, however, that we observe no strong evidence of standardization in our purchasing data. See Appendix A for detail.

2.3 Information Intervention

The information treatment considered in this study is one in which hospitals observe the distribution of other hospitals' prices and quantities and, in so doing, receive information about their relative performance in purchasing. In our empirical setting, sample hospitals were able to access information of this type in several ways: first, upon logging in to the subscription database, they were presented with a basic interface showing analytics regarding their relative performance. If they so chose, they could see the same analytics for specific products and could click through to access the underlying data used to construct the analytics. By repeating this step for each SKU purchased, member hospitals could construct the full purchase order database used in this study, though this process would require a great deal of patience due to the large number of SKUs each hospital purchases and to the daily download restrictions imposed by the web site.

The basic interface members access upon logging in presents graphical analytics for "potential savings" on each product the given member purchased in the previous year. Savings potential is determined by comparing members' prices to prices observed for all other members for the same exact product (SKU). These analytics are aggregated up to the supplier level in the main presentation, so that members can see how they are performing relative to peers separately for each manufacturer they have substantial purchasing arrangements with.

In order to analyze the effects of price transparency on negotiations, we obtained clickstream data on all members' website interactions. The data allow us to reconstruct the analytics a given member would have been presented with upon logging into the database, as well as the more granular data it would have been able to click through to access at each point in time.

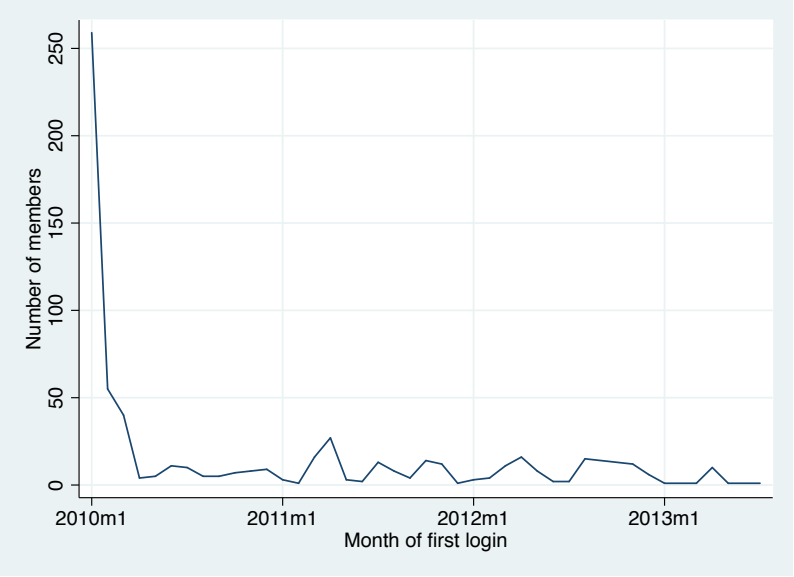
2.4 Identification of Information Effects

The ideal experiment that would enable us to empirically examine the effect of transparency on prices would be one in which some hospitals were randomly assigned to receive benchmarking data, while others were not. As noted above, the context that allows us to have this data is that the sample hospitals voluntarily joined a subscription database. The key feature of the data that allows us to estimate causal treatment effects of price transparency is that new members submit one year of retrospective data when they join the database, and continue to submit monthly data thereafter.

Thus, for hospitals that joined during the 2009-13 period, we observe data before and after they were first able to access the benchmarking information available in the database. Figure 5 shows the time series of hospitals joining the database between 2010 and 2013. One technical quirk of the data is that the database vendor rolled out a new version of its database in early 2010 and reinvited all current members to "join" at that point. Thus, for members "joining"

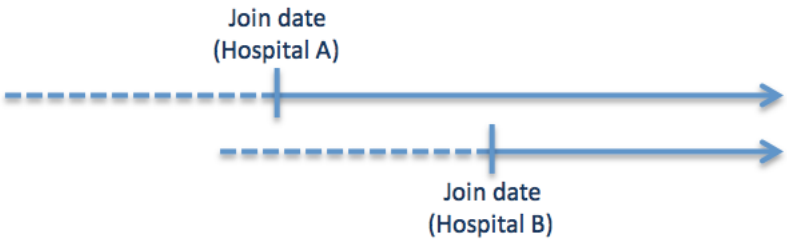
in early 2010, we cannot cleanly identify their pre-period and we exclude "pre-period" data for those members from each of our analyses. After March 2010, seven hospitals join the database in each month, on average.

Figure 5: Count of Hospitals Joining in Each Month



The availability of both pre- and post-join data for hospitals joining the database at different points in time allows us to use a differences-in-differences estimation strategy to estimate the treatment effect of having access to benchmarking information. The logic behind this identification strategy is illustrated in Figure 6. In our sample, there are no pure "control" hospitals – all hospitals by definition access the benchmarking data at some point. However, different hospitals join the database at different points in time. Suppose there are two hospitals, hospital A and hospital B, where A joined the database one period before hospital B. We would be able to isolate the treatment effect of joining the database on prices by comparing the price trends between the two hospitals for their overlapping time periods. In this example, the pre-join price observed for hospital A cannot separately be identified from a common shock to prices in that period. However, if we assume parallel trends between the two hospitals absent any information effects, any difference in price trends in the overlapping periods (one period pre- and post- hospital B joining the database, both of which are post-join for hospital A) can be attributed to the effect of information. To implement this identification approach, we estimate a differences-in-differences model controlling for time-invariant hospital-product price patterns and secular trends in stent prices. The latter control is particularly important, as prices decreased substantially over time during our period of interest; if we omitted controls for time trends, we would estimate large effects of access to information based solely on the large price drops observed between hospitals' pre- and post-information periods, which are likely to be due in large part to time trends.

Figure 6: Graphical Illustration of Identification Based on Timing of Join



The primary concern with this identification strategy is that timing of hospitals' joining the database may be correlated with other factors going on at the hospital contemporaneously that impact price trends. For example, hospitals may be inspired to join the database due to particular concerns about price trends, or (perhaps relatedly) they may concurrently be undertaking other initiatives intended to constrain prices, such as hiring new personnel or contracting other outside consulting services. These contemporaneous factors could bias our results upward or downward. To account for these potential issues, we also rely on an additional source of identification: new product entry. When a new product enters the market, initially no member will have data on other members' prices for that product. Benchmarking data will not become available for the new products until members submit their transactions data and they are loaded into the database (generally with a lag). New product entry thus gives us an additional point in time to observe the treatment effect of access to information.

Figure 7: Graphical Illustration of Identification Based on Timing of Join, New Product Join

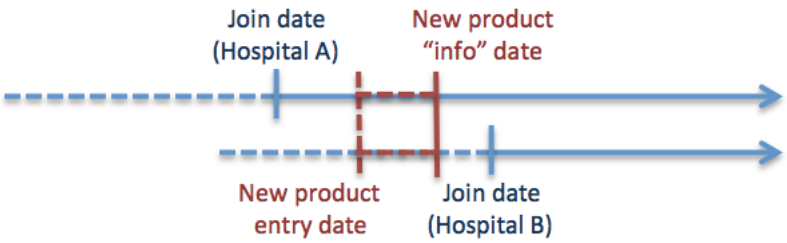
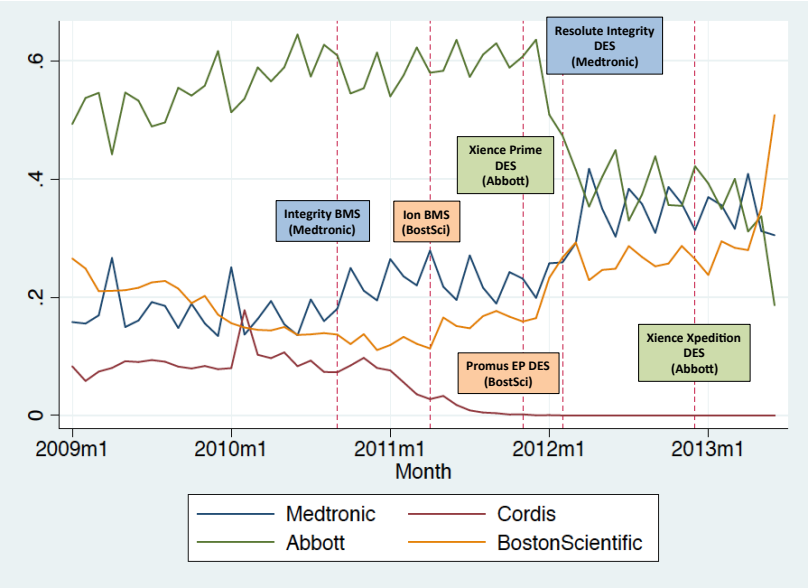


Figure 7 illustrates this identification strategy graphically. If timing of join is nonrandom based on the previously-described factors, such as other contemporaneous management changes, then we may question the differences-in-differences analysis above. However, if timing of join is plausibly random with respect to new product entry (and the effects of contemporaneous factors at the time of join are transitory), then we can identify the treatment effect of information by comparing pre-information and post-information prices to hospitals such as hospital A which are already in the database when a new product enters.

In Figure 8, we display the market share of each stent manufacturer over time, and note

the timing of entry of six new products between 2010 and 2013. Assuming timing of join is not endogenous with respect to new product entry (an assumption supported by Figure 5, in which we do not see spikes of join around the timing of entry), we can examine price trends around the timing of product entry to help identify causal treatment effects and to investigate sources of bias.

Figure 8: Market Share of Each Manufacturer, Relative to New Product Entry



3 Theory: Negotiated Prices and Using Benchmarking Information

Hospitals are typically reimbursed a fixed amount by private or public insurers for services they provide, and the inputs in our purchase order data are required to perform these services. Thus, these prices reflect costs that, at least in the short run, come directly from the hospital's bottom line. For this reason, hospitals are keen to find ways to reduce input costs, and the availability of benchmarking services offers one hope of doing so. As outlined briefly in the Introduction, to our knowledge no existing economic model addresses the primary ways in which market participants believe this type of transparency can affect price negotiations. While fully developing such theories is left for future work, in this Section we outline a simple model of negotiated prices as a point of departure and relate the main theoretical mechanisms suggested by market participants to the parameters of that model. In order to link this simple theoretical framework to the empirical analysis, we also describe the multiple steps involved in converting the information intervention (here, access to a database of benchmarking data) into meaningful changes in negotiated prices.

3.1 A Starting Point: Negotiated Prices Under Full Information

We first outline a full-information model of negotiated prices in order to help organize our thinking about the potential roles of bargaining, competition, information, and incentives in determining the price paid for any particular product j in a given hospital h in any month t. We use the pricing equations from the Nash Equilibrium of Nash Bargaining model first developed by Horn and Wolinsky (1988) and used in several recent empirical bargaining papers (Crawford and Yurukoglu (2012); Grennan (2013, 2014); Gowrisankaran, Nevo, and Town (2013); Ho and Lee (2014)). In the model, each hospital negotiates with each manufacturer separately and simultaneously, with each bilateral price maximizing the Nash Product of supplier profits and hospital surplus, taking the prices of potential substitute products as given. The price p_{jht} solves

$$\max_{p_{jht}} \quad [q_{jht}(\mathbf{p}_{ht})(p_{jht} - c_{jht})]^{b_{jt}(h)} \left[\pi_{ht}(\mathbf{p}_{ht}) - d_{jht}\right]^{b_{ht}(j)} \qquad \forall j \in \mathcal{J}_{ht}, \tag{1}$$

where the parameters $b_{jt}(h), b_{ht}(j) \geq 0$ represent the bargaining abilities of the supplier and hospital vis-a-vis each other, respectively, and d_{jht} is the hospital's disagreement payoff when no contract with j is signed. The supplier's disagreement payoff is equal to marginal cost under the assumptions that the hospital is a monopsonist, the supplier is not capacity constrained, and each hospital is small enough that any returns to scale in manufacturing or distribution are not affected by inclusion or exclusion from a single hospital. Taking the first-order conditions of Equation (1) yields the following pricing equation:

$$p_{jht} = c_{jht} + \frac{b_{jt}(h)}{b_{jt}(h) + b_{ht}(j)} \left[\left(1 + \frac{\partial q_{jht}}{\partial p_{jht}} \frac{p_{jht} - c_{jht}}{q_{jht}} \right) \frac{\pi_{ht} - d_{jht}}{q_{jht}} + p_{jht} - c_{jht} \right], \tag{2}$$

which says that equilibrium prices are equal to cost plus a markup. The markup equals the additional surplus created when the hospital contracts with product j versus when the hospital doesn't contract with product j multiplied by a fraction between zero and one given by the manufacturer's bargaining ability relative to that of the hospital. The elasticity term takes into account the fact that, conditional on successful contracting between supplier j and hospital h, the quantity of input product purchased will be determined by the physician's demand function. If physicians are price-sensitive in usage decisions, a dollar increase in price also results in a decrease in quantity, so it does not transfer linearly into manufacturer profits (and if demand is not price sensitive this term drops out). Equilibrium prices in this model are always between marginal cost and the supplier's Bertrand-Nash best-response price: equation 2 shows that price equals marginal cost when $b_j = 0$; and rewriting the same equation in the more standard markup and elasticity form yields $\frac{p_j - c_j}{p_j} = \frac{1}{-\frac{\partial q_j}{\partial p_j}\frac{p_j}{q_j} + \frac{b_h(j)}{b_j(h)}\frac{p}{(\pi_h - d_{jh})/q_j}}$, which is the same as Bertrand-Nash pricing when $b_h = 0$.

3.2 Direct and Indirect Roles of Benchmarking Information

Information about the prices paid for *the same product* at other hospitals $p_{jh'}$ could inform estimates of costs and/or supplier bargaining abilities[8]. These can be separately identified because bargaining abilities interact with marginal contributions, but costs do not. By contrast, information about the prices paid for *other products* at other hospitals $p_{kh'}$ could inform estimates of outside options.

In both cases, one would expect that hospitals would use information about the prices paid at other hospitals selectively and only when it benefits them. This suggests that, after providing such information, we might observe that many products show no change in price, and the probability and size of any price change would likely be increasing with the extent to which the price the hospital was paying was at the high end of the distribution. This is the one of the mechanisms industry participants discuss when they talk about the benchmarking database as a tool for a purchasing agent to search and collect market information for use in negotiations with suppliers.

Rather than (or in addition to) negotiators using the information on other hospitals' prices directly, the other way that industry participants describe using the benchmarking information is as a way for hospital managers to monitor the performance of purchasers and thus incentivize higher levels of effort in negotiations. This effort could be in using the data to be better informed, or at the negotiating table. In the case of higher effort in negotiations themselves, this would suggest a model where the hospital's bargaining ability parameter is not a fixed exogenous term, but the outcome of the agency problem faced by the hospital purchasing agent and hospital managers.

3.3 Steps from Access to Information to Changes in Negotiated Prices

While a hospital joining the benchmarking database has immediate access to the same data we do on the prices other hospitals are paying for any product, translating that access into differences at the negotiating table through either of the mechanisms outlined above still involves a series of steps: (1) Once a hospital joins the database, someone at the hospital must anticipate sufficient potential gains for a product to search the database for information regarding what other hospitals are paying. (2) The information found must then be useful in the sense that it suggests the hospital has an opportunity to negotiate a better price. Finally (3), the hospital must engage the supplier to negotiate a new contract (the term of the existing contract may not expire for up to a year or more). To the extent that each of these potential frictions have substantive costs in terms of time or resources, they will bias the ultimate effect of information on prices in different ways.

If there are any costs to searching for information in the database, then we would expect

[8] We focus on how variation in information on prices other hospitals are paying for same product (and other products) might enter the model for two reasons: (1) this is the exact type of exogenous variation in information that we observe and exploit in our empirical research design; and (2) we believe it is reasonable to think that uncertainty about supplier parameters would be larger than uncertainty about demand parameters at one's own hospital.

search efforts (and thus treatment effects) to be biased towards higher priced products that the hospital uses more frequently. Similarly, both the model where hospitals have uncertain beliefs about supplier parameters and also the model of purchasing manager agency suggest that the value of the price information found after searching the database could be greater when the hospital is paying a higher price relative to other hospitals for a product.

3.4 Potential Supply Side Effects

While demand side effects of information are generally null or beneficial to buyers, to the extent that suppliers know when buyers join the benchmarking database (or transparency is imposed via public policy), then supply side responses can negate or overturn these effects through greater obfuscation (Ellison and Ellison 2004), facilitating collusion (Albek et al. 1997), or forcing coordination not to price discriminate via secret discounts (Grennan 2013).

4 Estimating How Information Affects Negotiated Prices

Our baseline research design estimates the average treatment effect (ATE) of access to the database on negotiated prices, across all product-hospital combinations in the data. The estimate is based on the difference observed between pre-join and post-join prices, controlling for time-invariant price differences across hospital-product pairs and secular trends in stent prices. After the first quarter of 2010, the join date is relatively uniform over our sample period, so we can use variation in the timing of join to identify the price effect attributable to joining.

Letting P_{jht} denote the price observed for hospital h, product j, and month t, and controlling (as in all other subsequent specifications), for hospital-product fixed effects $[\theta_{jh}]$ and month fixed effects $[\theta_t]$, we estimate:

$$P_{jht} = \beta_{post} * \mathbb{1}_{\{post_{jht}\}} + \theta_t + \theta_{jh} + \varepsilon_{jht}$$

where β_{post} is the treatment effect of access to price information in the benchmarking database.

In these and subsequent results, we define and analyze two different versions of $post_{jht}$. The first, denoted the lower bound (LB) "post" variable, equals one in all periods after the given member first logs into the database, zero otherwise.[9] This is the price effect of simply having access to the database. The second, denoted the upper bound (UB) "post" variable, equals one in all periods after the given member first logs into the database *and* the given hospital-product

[9]For products that enter the market after a given hospital has joined the database, the member cannot access any benchmarking data on those products until the first round of transactions occur, are submitted to the subscription database organization, and the database organization loads the data into the database. Thus, the "post" variable for entering products does not equal one until the given hospital logs into the database after benchmarking data for those products has been loaded in. See further discussion of the "post" variable for new products below for detail.

is observed to have *any* price change; it equals zero otherwise. That is:

$$\begin{aligned}\mathbb{1}_{\{post_{jht,LB}\}} &= \mathbb{1}_{\{t \geq firstlogin_{jh}\}} \\ \mathbb{1}_{\{post_{jht,UB}\}} &= \mathbb{1}_{\{t \geq min\{t(reneg_{jh}) | t(reneg_{jh}) \geq firstlogin_{jh}\}\}}.\end{aligned}$$

The difference between the LB and UB treatment effects is intended to capture the effect of sticky contracts on prices; *even* if a hospital accesses the benchmarking database, learns that it is doing poorly in negotiations, and takes action internally to resolve poor performance (e.g., changing the incentive structure for the purchasing manager), prices cannot change until the supplier is engaged to renegotiate prices. The downside of this estimate is that it may mechanically be biased upwards in magnitude (to be more negative) if price changes are generally negative at any renegotiation. On the other hand, the LB price effect may understate the effect of information on price negotiation if there is a delay in price changes due to sticky contracts. In this Section, we show ATEs and conditional treatment effects for both the LB and UB "post" variables. In Section 4.2, we investigate potential "stickiness" in contracts directly by analyzing heterogeneity in lower bound ATEs using variables that proxy for renegotiation delays and costs.

We estimate this specification on the sample of all hospitals in the purchase order data that are observed to purchase stents. As discussed in Section 2.4, we drop "pre-join" data for hospitals who we observe to first log in to the database in Q1 2010, given that the vast majority of those hospitals most likely joined prior to 2010 and were simply re-invited to the new system. This leaves us with a sample of $350,891$ transactions for 385 hospitals. The estimated coefficient of interest in the baseline specification is shown in Table 3. The results for the specification as estimated with prices in levels (dollars) are shown in the first row; the specification is also estimated with prices in logs (second row) for the sake of comparison. In all other specifications, level (dollar) results are shown only for the sake of brevity.[10]

The lower bound estimate indicates that, across all hospital-product combinations, simply logging into the database has zero effect on average prices, and standard errors are small enough that we can reject an ATE of -$11 of joining the database on average prices. However, the upper bound estimate indicates that prices do decrease substantially once hospital-supplier pairs *renegotiate* after the hospital joins the database. The estimated effect of joining and renegotiating is that prices decrease by $50, or 4 percent. This effect is both statistically and economically significant; it slightly exceeds the amount by which prices would decrease if all hospital price fixed effects above the mean were brought down to the mean.

As discussed in Section 2.4, we may be concerned that our baseline analysis, leveraging timing of join for identification, may be biased due to other factors occurring at hospitals contemporaneous with them joining the subscription database. Our next analysis focuses specifically on entering products. As long as any differential price trends occurring at hospitals due

[10] Results are similar in direction and significance between all equivalent level and log specifications. Moreover, the price distribution plots in Section 2 indicate that negotiated prices are slightly skewed, but do not appear log-normal.

Table 3: Differences-in-Differences Results: ATE of Information on Prices

	Lower Bound TE	Upper Bound TE
[Price] β_{post}	-3	-50***
	(4)	(4)
[ln Price] β_{post}	0.0004	-0.041***
	(0.0026)	(0.0035)
DB Use	first login	first login
Fixed effects	transaction month, hospital-product	
$N = 350,891$ product(sku)-hospital-months.		
Standard errors clustered at hospital level.		

to factors concurrent with them joining the subscription database are transitory, these results will not be biased by endogenous timing of join. For this purpose, we exclude from the sample all products in the market at the beginning of 2010 and modify the specification to be the following:

$$\begin{aligned} P_{jht} &= \beta_{post} * \mathbb{1}_{\{post_{jht,entry}\}} + \theta_t + \theta_{jh} + \varepsilon_{jht} \\ \mathbb{1}_{\{post_{jht,entry}\}} &= \mathbb{1}_{\{t \geq min\{t(login_h) | t(login_h) \geq X \text{ months after } j \text{ entry}\}\}}. \end{aligned}$$

We set $\mathbb{1}_{\{post_{jht,entry}\}} = 0$ for the first X months after the product enters the market; in the following, we present results with $X \in \{2, 6\}$. Directly after product entry, data are entered into the database somewhat slowly. Two months after entry, at least ten hospitals' prices for the entering product would be available for benchmarking in the database. Six months after entry, there is far greater price information available – hospitals would be able to observe prices for at least 70 other hospitals for the entering product by that point. After X months post-entry, $\mathbb{1}_{\{post_{jht,entry}\}} = 1$ after the given hospital logs in to the database. At this point, we remain agnostic about how many hospitals' data are needed for a hospital logging in to believe they are observing actionable information, but it is likely that the six month cutoff would be more informative than the two month cutoff. To the extent that hospitals are in fact receiving actionable information about prices before the "post" variable equals one (that is, to the extent that they find a few hospitals' data informative enough to motivate renegotiation), our results will be biased toward zero.

The full sample difference-in-differences results, as well as the results when we limit the analysis to the 131, 181 transactions observed for the six products that enter the market during 2010-2013, are shown in Table 4. The lower bound effects are small, as in Table 3; for $X = 2$, the LB effect is -6 and not significantly different from 0, while for $X = 6$, the LB effect is -\$20 and statistically significant. For each $X \in \{2, 6\}$, the upper bound effects for new products only are significantly larger than in the full sample, indicating that prices decrease by \$60 to \$68 when hospitals are able to access prices on new products and subsequently renegotiate. The fact that the results for entering products are slightly larger indicates that treatment effects of price information in Table 3 are, if anything, biased slightly downward in magnitude due to contemporaneous factors at the timing of join. However, all specifications are of a similar

magnitude, reassuring us that any potential bias is not substantial.

Table 4: Differences-in-Differences Results: ATE of Information on Prices—New Products

	All Products		Entering ($X = 2$ mo)		Entering ($X = 6$ mo)	
	LB	UB	LB	UB	LB	UB
[Price] β_{post}	-3	-50***	-6	-60***	-20***	-68***
	(4)	(4)	(5)	(5)	(4)	(4)
Fixed effects	transaction month, hospital-product					
$N = 350,891$ (all) $N = 131,181$ (entering) product(sku)-hospital-months.						
Standard errors clustered at hospital level.						

4.1 Mechanisms: Where Does Information Matter Most?

We next consider differential transparency effects for specific hospital-product combinations that we expect ex ante to be particular targets of renegotiation effort for hospitals. First, we estimate a triple-differences model in which we interact our "post" variables with a dummy equalling one for the hospital's most popular (by market share) product prior to subscription. To the extent that renegotiation is costly, we expect hospitals to focus their effort on renegotiating prices for products that are relatively more important to them upon receiving price information. The specification we estimate is

$$\begin{aligned} P_{jht} &= \beta_{post} * \mathbb{1}_{\{post_{jht}\}} + \beta_{post,pop} * \mathbb{1}_{\{post_{jht}\}} * \mathbb{1}_{\{pop_{jh,pre}\}} + \theta_t + \theta_{jh} + \varepsilon_{jht} \\ \mathbb{1}_{\{pop_{jh,pre}\}} &= \mathbb{1}_{q_{jh,pre} \geq max_k\{q_{kh,pre}\}}. \end{aligned}$$

where $\mathbb{1}_{\{pop_{jh,pre}\}}$ is a dummy for the most popular product purchased by hospital h before it joined the database. The results for the full sample and for entering products only are shown in Table 5. The lower bound treatment effect is larger for popular products vs. baseline in each of the three specifications estimated, by about $\$20 - \$30$, indicating that preferred products are more likely to experience price decreases post-transparency than other products. The upper bound treatment effect interaction is of a similar magnitude in each specification, ranging from -$23 to -$34, but it is not always statistically significant. To the extent that differential UB price decreases for popular products are smaller in (relative) magnitude than LB price decreases, this may be due to popular products being renegotiated earlier and/or more often than other products.

Second, we estimate a triple-differences model in which we allow for different treatment effects for products and hospitals in different parts of the price distribution. We expect that hospitals will be most likely to direct renegotiation effort toward products for which they learn there are the largest potential savings based on observed prices when they first log in to the database. In this analysis, we investigate this hypothesis by looking for differential treatment effects among product-hospitals in higher parts of the price distribution. Accordingly, for each member's first login to the database, we compare the member's price for each product purchased in the year prior to login to the full distribution of prices for the same product

Table 5: Triple Differences Results: Treatment Effect of Information on Prices for Most Preferred Products

	All Products		Entering (2 mo)		Entering (6 mo)	
	LB	UB	LB	UB	LB	UB
[Price] β_{post}	7	-44***	0	-57***	-15***	-65***
	(4)	(4)	(4)	(4)	(4)	(4)
[Price] $\beta_{post,pop}$	-28***	-23***	-21*	-24	-28***	-34
	(9)	(10)	(13)	(19)	(12)	(21)
Fixed effects	transaction month, hospital-product					
$N = 350,891$ (all) $N = 131,181$ (entering) product(sku)-hospital-months. Standard errors clustered at hospital level.						

across all hospitals during the same period. We then flag each product-hospital pair based on its pre-join price relative to percentiles of the price distribution:

$$\begin{aligned} P_{jht} &= \beta_{post} * \mathbb{1}_{\{post_{jht}\}} + \beta_{post}^{highX} * \mathbb{1}_{\{post_{jht}\}} * \mathbb{1}_{\left\{high_{jh,pre}^{X}\right\}} + \theta_t + \theta_{jh} + \varepsilon_{jht} \\ \mathbb{1}_{\left\{high_{jh,pre}^{X}\right\}} &= \mathbb{1}_{P_{jh,pre} \geq prctileX\{P_{jh',pre}\}_{h'=1}^{H}} \end{aligned}$$

for various values of X indicating different percentiles of the pre-join price distribution. That is, the coefficient β_{post}^{high25} will capture the differential treatment effect of transparency on prices for product-hospitals which were above the 25^{th} percentile of the price distribution in the year just prior to joining.

The results in Table 6 show separate triple-differences results for the 25^{th}, 50^{th}, and 75^{th} percentiles. Here, we observe striking evidence that the lower bound treatment effects described above concealed substantial heterogeneity. The differential treatment effect for higher parts of the price distribution is monotonically increasing as we move to higher percentiles. Hospital-products above the 25^{th} percentile pre-join have a differential treatment effect of -$5, compared to -$14 for the 50^{th} percentile and -$32 for the 75^{th} percentile. This evidence is consistent with hospitals who learn in the database that they are doing particularly poorly in negotiating being more likely to attempt renegotiation or to exert effort in bargaining once the supplier is engaged in renegotiation. It is also worth noting that we do not see evidence that the lower part of the distribution shifts upward significantly, which would be suggestive evidence of mean reversion (we define the interaction term based on previous periods' prices). The upper bound effects indicate that even the lowest part of the price distribution shifts down slightly (-$24 for hospital-products below the 25^{th} percentile), and effect sizes are monotonically increasing as we look to higher points in the price distribution – the total UB treatment effect for hospital-products above the 75^{th} percentile is -$110.

In sum, the evidence for hospitals' most popular products and for hospital-products with the highest prices pre-join indicate that the treatment effects of information are largest exactly where we most expect to see them – among products with the largest budgetary impact on hospitals ex ante, and in hospital-products with the largest potential savings.

Table 6: Triple Differences Results: Treatment Effect of Price Information on Different Parts of the Price Distribution

	p25		p50		p75	
	LB	UB	LB	UB	LB	UB
[Price] β_{post}	1	-24***	4	-27***	4	-33***
	(6)	(6)	(5)	(5)	(5)	(5)
[Price] $\beta_{post,high}$	-5	-38***	-14	-55***	-32***	-77***
	(8)	(9)	(9)	(10)	(12)	(11)
Fixed effects	transaction month, hospital-product					
$N = 253,513$ product(sku)-hospital-months.						
Standard errors clustered at hospital level.						

4.2 Heterogeneity in LB Effects and Renegotiation

Finally, as noted above, we are concerned that upper bound estimates may be biased due to mechanical issues with conditioning on renegotiation. For example, if prices mechanically trend down over time, then these estimates will be biased upward in magnitude. In this Section, we investigate the connection between the LB and UB effects as it relates to potential "stickiness" of contracts. Specifically, we investigate the hypothesis that, if contracts are indeed "sticky," then our LB estimates will be biased downward due to the "post" period containing several months of data for which the prices are effectively fixed. We estimate specifications wherein we drop from the sample the first X months after the hospital first logs in to the database, thus estimating the LB treatment effect by comparing pre-join prices to prices after the hospital joins the data and has X months to engage the supplier in renegotiation. Motivated by the findings in Section 4.1 that effort in renegotiating may be concentrated among products with the largest budgetary impact for a given hospital, we estimate these specifications both on average and allowing for differential effects for popular products.

The results are shown in Table 7. The first row of the Table shows the ATEs across all products when the first $X \in \{6, 9, 12\}$ months of data after the hospitals logs in to the database are dropped. As expected, effect sizes are increasing in X, which is suggestive of LB effects with $X = 0$ being biased downward due to sticky contracts; however, the standard errors are large. The second and third rows are the baseline and interaction estimates of the specifications where we allow differential effects for popular products. The results for popular products, for which we have the best ability to detect LB treatment effects, are striking. They increase monotonically as we move to higher values of X to account for delays in renegotiation. Notably, the effect for $X = 12$ among popular products equals -\$53; that is, if we look for treatment effects in products where they are most likely to appear and allow for them to materialize slowly over time due to contract stickiness, the lower bound treatment effect is very similar to upper bound treatment effects where we condition on renegotiation.

Table 7: LB Result Heterogeneity: Allowing for Delay in Renegotiation

	Omitting the First X Months:		
	$X = 6$	$X = 9$	$X = 12$
	LB	LB	LB
[Price] β_{post}	-6	-6	-9
	(3)	(5)	(6)
[Price] β_{post}	2	2	-1
	(3)	(5)	(6)
[Price] $\beta_{post,pop}$	-38***	-41***	-54***
	(10)	(12)	(14)
N	298,121	248,067	208,593
Fixed effects	month, hospital-product		
Standard errors clustered at hospital level.			

5 Conclusion

This paper conducts one of the first studies of the impact of information in negotiated price markets, motivated by the rise in benchmarking data services marketed towards buyers in business-to-business markets and calls for greater transparency in these markets by policymakers. Our empirical study is done in the context of hospital supply purchasing, an area where there has been keen interest in information as a way to decrease hospital supply costs. We use new data on all purchase orders issued by over ten percent of US hospitals from 2009-13 and a differences-in-differences research design to compare the prices negotiated by hospitals with and without benchmarking information on what other hospitals pay. The estimated ATE of this type of information across product-hospital-months for coronary stents ranges from a lower bound (based on access to the benchmarking data) of zero to an upper bound (based on access plus a renegotiation occurring) of four percent savings. We interpret this gap between upper and lower bounds as evidence of substantial frictions between access and meaningful use of benchmarking data, and we show suggestive evidence that this is the case by investigating timing of lower bound treatment effects.

To better understand these frictions and inform both policy and future theory, we estimate conditional average treatment effects based on the expected returns to and the realized value of information in the database for each product-hospital pair. For a hospital's most frequently used stent, the treatment effect is about 2 percentage points larger at both upper and lower bounds, suggesting that searching and/or using the data is costly in some way that makes it more useful for more frequently used products where the economic gains are expected to be larger. Further, we find that treatment effects are 2.5 percentage points (lower bound) and 5 percentage points (upper bound) larger when the price a hospital is paying for a given product is above the 75th percentile of the prices paid by all hospitals in the data, suggesting, consistent with intuition, that benefits to using the data are increasing in the price paid relative to others. Interestingly, this pinch from the top of the price distribution is accompanied by a 2 percent shift down in the price distribution that holds even for hospitals paying prices below the 25th percentile, which seems more likely to be consistent with a model of benchmarking data as a

tool for monitoring and incentivizing employees engaged in negotiations rather than imperfect information about supplier parameters.

While our results suggest that on net policies or intermediaries that increase transparency may indeed lower the prices hospitals pay for medical supplies, our hope is that this study opens more doors than it closes. Coronary stents are just one product category (albeit an important one), and the results are likely to be different for different medical products, let alone for different industries. While our data contains purchase orders for nearly 3,000 categories and 2 million product SKUs, analysis of other product categories using this price and quantity data alone may be complicated by the impact of unobserved nonlinearities or bundling in contracts. We believe this reinforces the need for more data collection and theory development.

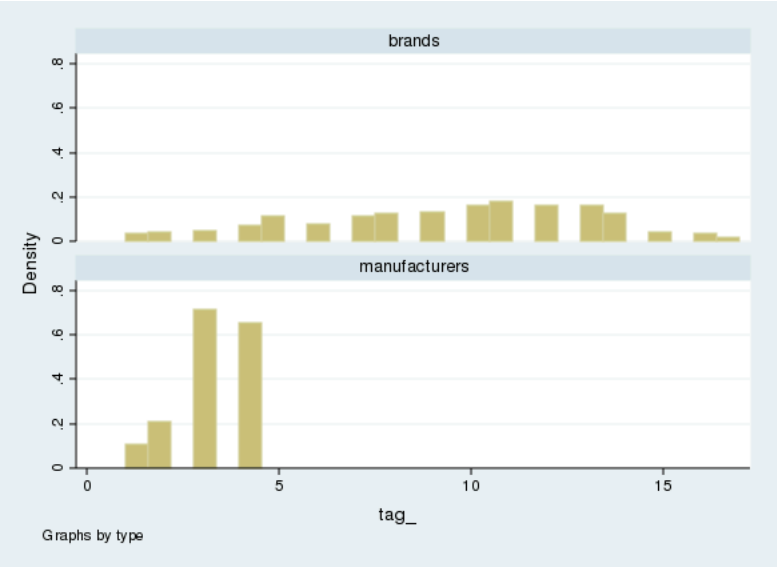
In the large existing theory on bargaining and incomplete information, we were surprised that no model quite captured the main phenomenon of interest here. We see modeling frictions in the use of information and the potential for information to affect within-firm agency frictions in negotiation as two especially interesting areas suggested by our analysis for future theory development.

Appendices

A Checks for Standardization and Share-based Contracts

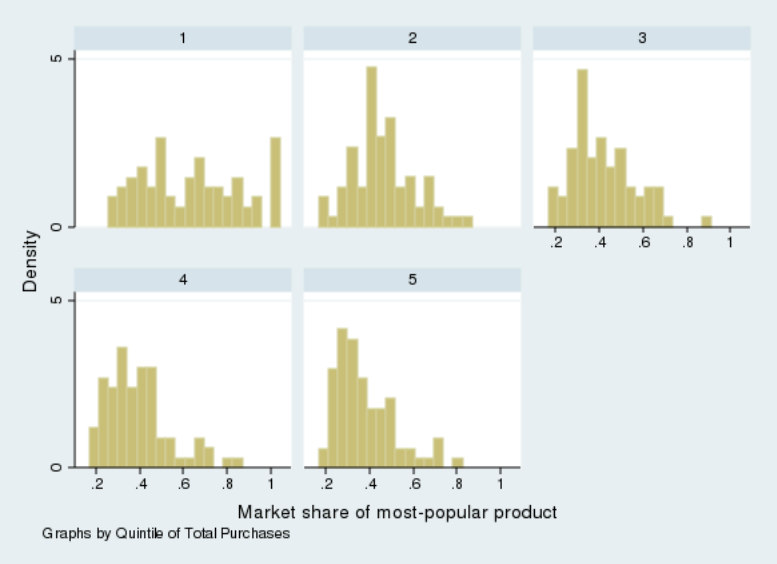
In Figure 9, we show histograms of total manufacturers and total stent brands purchased by each hospital in the sample – the vast majority of hospitals purchase multiple brands from multiple manufacturers, rather than purchasing a single most-preferred product for the whole facility.

Figure 9: Histograms – Number of Brands/Manufacturers per Hospital



As a practical matter, stents tend to have simple contracts, so that we can be confident our transactions data captures real prices—we cannot observe volume or market share rebates in the data, so to the extent such rebates were common we would have substantial measurement error. Figure 10 gives some reassurance on this point, showing a histogram of the market share of each hospital's most-preferred product, grouping hospitals by quintile of overall stent volume purchased. We observe very little evidence of hospitals bunching at market share thresholds where we would expect to see market share rebates be awarded (for example, 80 percent, 75 percent, etc.), as would be expected if nonlinear contracts were popular in the sample.

Figure 10: Market Share of Most-Preferred Brand, by Quintile of Purchase Volume



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References

[Albek et al., 1996] Albek, S., Mollgaard, P., and Overgaard, P. (1996). Law-assisted collusion? the transparency principle in the danish competition act. *European Competition Law Review*.

[Bronnenberg et al., 2014] Bronnenberg, B., Dube, J.-P., Gentzkow, M., and Shapiro, J. (2014). Do pharmacists buy bayer? informed shoppers and the brand premium.

[Crawford and Yurukoglu, 2012] Crawford, G. and Yurukoglu, A. (2012). The welfare effects of bundling in multichannel television. *American Economic Review*, 102(2).

[Ellison and Ellison, 2009] Ellison, G. and Ellison, S. (2009). Search, obfuscation, and price elasticities on the internet. *Econometrica*, 77(2):427–452.

[Gowrisankaran et al., 2014] Gowrisankaran, G., Nevo, A., and Town, R. J. (2014). Mergers when prices are negotiated: Evidence from the hospital industry. forthcoming in the American Economic Review.

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

[Grennan, 2014] Grennan, M. (2014). Bargaining ability and competitive advantage: Empirical evidence from medical devices. forthcoming in Management Science.

[Ho and Lee, 2014] Ho, K. and Lee, R. S. (2014). Insurer competition and negotiated hospital prices. NBER working paper 19401.

[Horn and Wolinsky, 1988] Horn, H. and Wolinsky, A. (1988). Bilateral monopolies and incentives for merger. *RAND Journal of Economics*, 19:408–419.

[Jin and Leslie, 2003] Jin, G. and Leslie, P. (2003). The effect of information of product quality: Evidence from restaurant hygiene grade cards. *Quarterly Journal of Economics*, 118(2):409–451.

[Sorenson, 2000] Sorenson, A. (2000). Equilibrium price dispersion in retail markets for prescription drugs. *Journal of Political Economy*, 108(4).