Price Discrimination and Bargaining: Empirical Evidence from Medical Devices

Matthew Grennan*
University of Toronto, Rotman School of Management
matthew.grennan@rotman.utoronto.ca

October 31, 2011

Abstract

Many important issues in business-to-business markets involve price discrimination and negotiated prices, situations where theoretical predictions are ambiguous. This paper uses new panel data on buyer-supplier transfers and a structural model to empirically analyze bargaining and price discrimination in a medical device market. While many phenomena that restrict different prices to different buyers are suggested as ways to decrease hospital costs (e.g., mergers, group purchasing organizations, and transparency), I find that: (1) more uniform pricing works against hospitals by softening competition; and (2) results depend ultimately on a previously unexplored bargaining effect.

*Data for this research was provided by Millennium Research Group (www.mrg.net). Special thanks for the guidance and encouragement throughout this research project go to my dissertation committee: John Asker, Adam Brandenburger, Allan Collard-Wexler, Michael Katz, and Bernie Yeung. I also benefited from discussions with Victor Aguirregabiria, Heski Bar-Isaac, Luís Cabral, Ken Corts, Catherine de Fontenay, JP Eggers, Avi Goldfarb, Mara Lederman, Robin Lee, PT Leger, Hong Luo, Matt Mitchell, Gabriel Natividad, Ariel Pakes, Rob Salomon, Gus Stuart, Ali Yurukoglu, and seminar audiences at Analysis Group, Arizona, Columbia, Georgia, HEC Montreal, LSE, NYU, Northwestern (Kellogg), Rochester (Simon), Toronto (Rotman), and Yale SOM. Andy Cron, John Brumleve, Mark Bly, Rob Tumarkin, and many others have been helpful in teaching me about medical device manufacturing and sales. Physicians and administrators at NYU Medical Center and CGH, Sterling, IL were especially generous with their time and knowledge regarding hospital purchasing and the inner workings of a cardiac catheterization lab. Some industry background research was conducted while attending the Transcatheter Cardiovascular Therapeutics 2008 conference, which was made possible by the Cardiovascular Research Foundation.

1 Introduction

In business-to-business markets, prices are often negotiated. This can result in different buyers paying substantially different prices for the same product from the same supplier. Whenever some buyers are able to get "a better deal" than others in this way, policy-makers, potential middle-men, and other buyers naturally wonder if interventions that move towards more uniform prices might make buyers better off. This paper estimates the welfare effects of different hospitals paying different prices—and several interventions that would make prices more uniform—in the market for coronary stents, a "blockbuster" medical device on which hospitals spend over $5 billion each year.

The price of medical technologies, such as coronary stents, is often cited as a driver of the increasing costs of healthcare (Keehan et. al. 2011). Many of the interventions intended to lower these costs impose restrictions that would make prices more uniform, but the actual effects of these interventions on prices and welfare are not well-understood. For example, hospital mergers make prices more uniform by creating a single buyer from several. Though a common justification for hospital mergers is to lower input costs, evidence that they do so has been mixed (Dranove & Lindrooth 2003). Group purchasing organizations (GPOs)—where a group of buyers delegate purchasing authority to a third party—also make prices more uniform, and they permeate much of hospital purchasing. However, the actual value provided by GPOs is a constant topic of debate, especially in the market for coronary stents and other "physician preference items" (Burns & Lee 2008). The recent healthcare reform efforts in the United States have brought calls for greater market transparency, with many anticipating that such reform would lead to more uniform prices across hospitals, but mixed predictions as to who might benefit (Kyle & Ridley 2007). The lack of consensus regarding the impact of these interventions on the cost of critical healthcare inputs is driven in part by the fact that economic theory alone offers ambiguous predictions, and necessary data are difficult to procure.

This paper uses new panel data on the prices and quantities transferred between hospitals and coronary stent manufacturers to estimate a structural model of supply and demand that incorporates bargaining over prices. I then use the estimated model to compare welfare outcomes under the current pricing regime (where different hospitals pay different prices for the same stent) and counterfactual regimes with transparency, group purchasing, and mergers. I find that: (1) in this market, more uniform pricing actually works against hospitals through a competition softening effect; and (2) results depend ultimately on a previously unexplored bargaining effect. Whether a given intervention will raise or lower stent prices hinges on the details of how it unlocks these two forces.

The way in which a change to more uniform pricing affects competition relates directly to the theory of price discrimination with oligopoly.[1] If hospitals are more vertically differentiated from one another in their preferences for stents (what the literature would call best-response symmetry among manufacturers), then competition will tend to intensify with more uniform prices (Holmes 1989). If hospitals are instead more horizontally differentiated (best-response *a*symmetry), then competition will tend to soften with more uniform pricing, as manufacturers price to their captive markets (Corts 1998). Thus understanding if different prices are good or bad for hospitals requires knowing first how much variation in price is due to variation in demand, and then whether this demand variation is vertical or horizontal. A complete analysis requires going further and accounting for the fact that prices are not "set" by suppliers as they are in the price discrimination literature—stent prices are negotiated.

When buyers and suppliers negotiate prices, supplier costs, buyer willingness-to-pay, and competition determine only a range of potential prices (versus a single price) for each buyer and supplier.[2] The final price will depend on what I refer to as each firm's *bargaining ability*—the ability to reach a more favorable point within that range. Heterogeneity in bargaining abilities turns out to be important in explaining the variation in prices for the same stent sold to different hospitals—as one hospital purchasing manager put it, "There is a lot of wiggle room [in prices]." Further, this importance of variation in bargaining ability means that a complete understanding of any market intervention will require understanding how it affects bargaining abilities, in addition to competition.

Despite the ambiguity of the predictions from theoretical work on price discrimination and bargaining, the empirical literatures in these areas are still relatively small. This is largely because empirical studies of business-to-business markets (where both often occur) have been limited by the difficulty of accessing data on transfers between buyers and suppliers. Of the recent empirical studies involving price discrimination (Duggan & Scott-Morton 2006; Hastings 2008; Villas-Boas 2009), bargaining (Dranove et al. 2008; Dafny 2009; Ho 2009; Crawford & Yurukoglu 2010), and vertical contracting relationships more generally (Ho, Ho, & Mortimer 2010), only Hastings (2008) and Dafny (2009) have had access to data on the actual buyer-supplier transfers. Hastings (2008) looks at the effects of price discrimination versus uniform pricing between gasoline stations and wholesalers, but does not consider bargaining. Dafny (2009) is interested in diagnosing the presence of market power among providers of employee health insurance, but not analyzing bargaining or price discrimination per se. This paper builds on previous

[1] Stole (2007) and Armstrong (2008) offer excellent reviews of this large literature.

[2] The simplest example is bilateral monopoly, where the buyer won't pay a price above its willingness-to-pay, and the seller won't sell for a price less than its cost. With a competing supplier, the buyer has an outside option that lowers the top of this range, but as long as the competing product is not a perfect substitute, there will still be a range of prices at which the buyer and supplier could trade.

empirical and theoretical research by quantifying several mechanisms previously illustrated in theory and demonstrating new interactions between price discrimination and bargaining in a context where both are important.

Central to this study is an unusually detailed panel data set, providing the quantities purchased and prices paid for all coronary stents sold to 96 U.S. hospitals from January 2004 through June 2007, at the stent-hospital-month level. The stent market is a business-to-business market in which hospitals generate revenue by implanting stents during angioplasty procedures, and the stent is a necessary input that the hospital must purchase from a device manufacturer. Contracts are negotiated, stipulating the price at which the hospital can purchase a given stent over a specified period of time, and different hospitals negotiate different prices for the same stent. This price variation has significant implications for profits. Moving from the 25^{th} to 75^{th} percentile in price would result in a change of about $300,000 annually (about four nurses' salaries) at the average-sized hospital. Section 2 of the paper provides more details regarding the industry and data.

Even with these detailed data, several important variables—cost, willingness-to-pay, and bargaining ability—are unobserved. Further, separating the impact of demand and competition on the range of potential prices from the impact of bargaining abilities within that range requires an explicit model of how competition and bargaining determine prices. In Sections 3 and 4, I address these challenges with a structural empirical approach, similar to Berry, Levinsohn, & Pakes (1995), but using a pricing model that generalizes the standard Bertrand-Nash price-setting model to allow for bargaining over prices. The model has two parts: (1) a model of doctor demand for coronary stents uses the price and quantity data to estimate demand for each stent in each hospital in each month; and (2) a model of how prices emerge from competition and bargaining uses the demand estimates and the price and quantity data to estimate costs and relative bargaining abilities for each stent in each hospital in each month.

On the demand side, a random coefficients discrete choice model incorporates heterogeneity in preferences for stents across hospitals, physicians, and patients. The fact that prices are fixed in long-term contracts provides two new sources of identification: First, doctor preferences evolve over time while prices remain fixed; so when prices are renegotiated, the movement is along the demand curve. Second, bargaining ability provides a new supply shifter. The demand estimates agree with anecdotal evidence that doctors are slightly price-sensitive, are brand-loyal, and can differ widely in their preferences over the different stents available on the market.

Given the demand estimates, I estimate cost and bargaining ability parameters using a pricing model in which each stent manufacturer and hospital engage in bilateral Nash Bargaining, and these bilateral outcomes form a Nash Equilibrium with each other.

This model relates to the theoretical literature on bargaining with externalities (Horn & Wolinsky 1988), and Crawford & Yurukoglu (2010) use a close variant in an empirical setting. I solve the model for the equilibrium pricing equation, which is useful in two ways: First, it clarifies how this bargaining model is a generalization of the standard Bertrand-Nash differentiated products pricing model, providing a tight link to theoretical work on price discrimination. Second, it shows that price is equal to cost plus a margin that depends on bargaining abilities, elasticities, and the marginal contribution of each product relative to its competitors, making it clear how covariation in price and demand can identify bargaining ability parameters separately from costs. The estimates show that allowing for heterogeneity in bargaining abilities in addition to heterogeneity in demand is critical for explaining the price variation observed in the data.

The heterogeneity across hospitals in demand and bargaining abilities also play quantitatively important roles in the counterfactual changes due to transparency, group purchasing, and mergers considered in Section 5. Because different hospitals have doctors with different brand loyalties (variation in hospital demand is more horizontal than vertical), a change to more uniform pricing will soften competition as suppliers price to extract surplus from their captive hospitals. As a result, any intervention that intends to lower prices through making them more uniform must be accompanied by an increase in hospital bargaining ability. I estimate that this required increase can be rather large. In a GPO made of all hospitals, the bargaining ability of the GPO would have to be above the 70^{th} percentile of the individual hospital bargaining abilities.

Section 5.3 extends the analysis to 100 merger simulations among groups of randomly selected hospitals. These merger experiments inform the conditions under which multi-hospital systems might be able to decrease stent prices, and in doing so generate a deeper understanding of the competitive and bargaining effects. The randomly selected hospitals for each merger have varying amounts of symmetry in their preferences. I develop a measure of the extent of (a)symmetry and quantify its relation to merger outcomes. For simulations with post-merger bargaining abilities equal to the mean of the merging hospitals, a one standard deviation increase in symmetry leads to a 1.3% increase in hospital surplus. There is also a complementarity between the competitive and bargaining effects: The importance of symmetry more than doubles when the post-merger bargaining ability is the maximum of the merging hospitals.

While this paper focuses on the market for coronary stents, price variation across different buyers for the same product—and proposals to restrict it—occur in a variety of markets. Many aspects of the approach used here are flexible enough to be applied to other settings. However, the credibility of any structural study depends on capturing important industry-specific details, which are the topic of the next Section.

2 Coronary Stents: Industry Description and Data

The coronary stent industry is not only an example of a business-to-business market, it is also interesting and important in and of itself. The coronary stent is a medical device used in angioplasty, an important treatment for blockages in the arteries surrounding the heart (a condition known as coronary artery disease). These blockages can cause pain, loss of mobility, and eventually heart attack, making coronary artery disease the leading cause of death in the United States.[3] Angioplasty is a minimally invasive technique in which the doctor threads a balloon-tipped catheter from an access point (usually the femoral artery near the groin) to the heart. Using imaging devices, the doctor positions the balloon tip across the blockage, and expands the balloon, compressing the blockage to the artery walls. A stent is a small metal tube that is then placed via catheter where the blockage was cleared and left in the body as structural support for the damaged artery wall. Though angioplasty is attractive due to its minimally invasive nature, traditional stainless steel "bare-metal stents" (BMS) have the drawback that scar tissue growth around this foreign body can lead to significant renarrowing of the artery in about 33% of cases. "Drug-eluting stents" (DES) attempt to remedy this problem by coating the stent with a drug that discourages scar tissue growth, and they have been successful in reducing the incidence of renarrowing to about 9%.[4]

2.1 The "Economics" of the Stent Market

With the introduction of DES, stents became the first medical device to reach revenue levels similar to those of a "blockbuster" drug. The three million stents implanted worldwide each year generate annual revenues of more than $5 billion to stent manufacturers and $30 billion to hospitals and doctors for the stenting procedures.

Hospitals and doctors generate revenue from each angioplasty procedure, usually via reimbursement from a patient's insurer. The reimbursement rates are negotiated by the hospital with each insurer (usually taking Medicare rates, which are not negotiated, as a starting point), so they vary across hospitals and across insurers for each hospital.[5] The average Medicare reimbursement rates for a basic stenting procedure are $812 for the

[3]U.S. Department of Health & Human Services, National Institutes of Health, National Heart Lung and Blood Institute Diseases and Conditions Index. www.nhlbi.nih.gov/health/dci/Diseases/Cad/CAD_WhatIs.html (June 2008)

[4]Robert J. Applegate, "Drug-Eluting Stents: The Final Answer to Restenosis?" Wake Forest University Medical Center, http://www1.wfubmc.edu/articles/CME+Drug-eluting+Stents (September 15, 2008)

[5]Because the data set used in this paper is sold as market research to the device manufacturers, hospitals are anonymous, which, unfortunately, prevents linking this data set with other data sources on the hospitals.

doctor, regardless of the type of stent used; and for hospitals, \$10,422 for a BMS and \$11,814 for a DES.[6] Reimbursements do not depend on the manufacturer of the stent.

Out of this revenue comes the hospital's costs, including the cost of any stents used. Thus the hospitals keep in profit any price savings they can achieve on the cost of stents. While in many markets there might be some interaction between the costs negotiated with suppliers and the revenues negotiated from buyers, that is not the case here. For Medicare patients, who receive over 50% of all stenting procedures, the reimbursement levels are fixed; and the reimbursements from private insurers are generally negotiated as a markup on Medicare rates across all procedures performed at the hospital. Thus reimbursement levels at each hospital are fixed with respect to the cost of stents.

2.2 Data Overview

The data set used in this paper is from Millennium Research Group's *Marketrack* survey of catheter labs, the source that major device manufacturers subscribe to for detailed market research. The goal of the survey is to provide an accurate picture of market shares and prices by U.S. region (Northeast, Midwest, South, West).[7] The U.S. market is dominated by four large multinational firms: the Abbott Vascular (formerly Guidant) division of Abbott Laboratories, Boston Scientific, Johnson & Johnson's Cordis division, and Medtronic, which together make up over 99% of U.S. coronary stent sales.[8] These manufacturers offered a total of nine BMS and two DES during the sample period.

The key variables in the data are the price paid and quantity used for each stent in each hospital in each month. In addition, the hospitals report monthly totals for different procedures performed, such as diagnostic angiographies, and prices and quantities for other products used in the catheter lab, such as balloon catheters and guiding catheters. After removing hospitals with incomplete reporting (usually failure to report price data—see Appendix A for details), the data set I use for analysis is an unbalanced panel of 10,098 stent-hospital-month observations at 96 U.S. hospitals over 42 months from January 2004 through June 2007.

Figure 1 shows aggregate trends in quantities and prices over the sample period. In March 2004, a second DES entered the market, resulting in decreased prices and increased usage of DES. In 2006, a study questioned the safety of DES, resulting in less DES usage

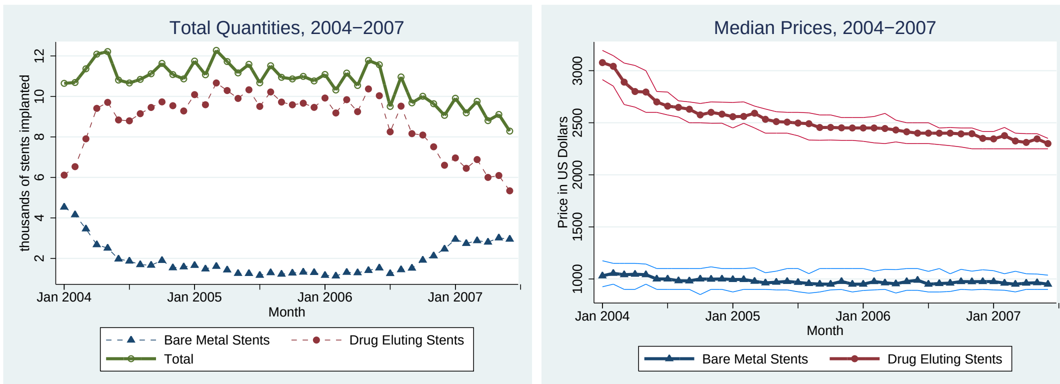
[6] By "basic" I mean single-vessel operations with no "modifiers" for difficulty of the procedure, location of the hospital, etc. These numbers represent the lower bound in revenue for these procedures (Medicare upper bounds are roughly 1.5 times these payments, and private insurers generally reimburse at even higher levels). Numbers from *Federal Register*, Volume 68, No. 216, November 7, 2003; and *Federal Register*, Volume 68, Number 148, August 1, 2003.

[7] See www.mrg.net for more details on the survey.

[8] iData Research, Inc. "US Markets for Interventional Cardiology" (2006).

Figure 1: Aggregate trends in the market over the sample period. The quantity graph shows the total number of stents implanted, also broken down into DES and BMS. The price graph shows median prices of BMS and DES (the thin lines are the first and third quartiles).

(a) Quantities **(b)** Prices



and less stenting overall. This trend later reversed as it became clear that DES were not as dangerous as the study suggested, but the response to the scare provides useful variation to help identify the shape of the demand curve.[9]

2.3 Cross-sectional Variation

Table 1 provides price summary statistics, documenting the variation in prices across hospitals. The coefficient of variation (standard deviation over mean), a common measure of price dispersion, has a mean of 0.13 in the sample. For example, one of the best-selling stents, DES1, has a mean price of \$2508 with a standard deviation of \$317.

Table 1: Price variation across hospitals. The table reports summary statistics for the distribution of price (\$US) across hospitals for each stent. The sample is restricted to September 2005 (middle of the sample in time) to isolate cross-sectional variation. There are N=54 hospitals sampled, and BMS1-3 have exited the market.

	mean (\$)	std. dev. (\$)	std.dev./mean	min (\$)	max (\$)	N
BMS4	1006	175	0.17	775	1500	25
BMS5	926	191	0.21	700	1600	23
BMS6	952	156	0.16	775	1475	26
BMS7	1035	174	0.17	775	1600	39
BMS8	1063	338	0.32	800	1950	11
BMS9	1088	224	0.21	800	1800	47
DES1	2508	317	0.13	2100	3280	54
DES2	2530	206	0.08	2150	3195	54

[9] For an overview of the DES scare and its aftermath, see "Embers still smoldering from the 2006 ESC firestorm, as experts mull DES safety and efficacy" at www.theheart.org/article/996053.do.

These per-unit price differences translate into significant dollar amounts. A \$317 change in price results in a difference in cost of over \$300,000 per year in the mean-volume hospital, or nearly \$1 billion per year across the three million stents implanted worldwide. This is about 20% of the annual revenue of the global stent market.

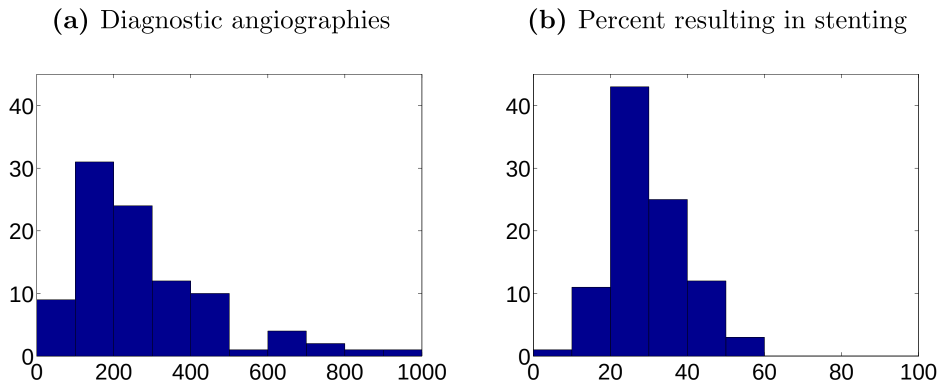
There are many potential explanations for this price variation across hospitals. Revenue for stenting procedures varies across hospitals. The relative strength of the interventional cardiologists versus substitute treatments and the distribution of patient types will vary across hospitals as well. Also, stents are differentiated products, and doctors vary in their preferences over which stent is best to treat a given patient. These variations induce different competitive environments in different hospitals. The variation in the market shares of each stent, the number of diagnostic procedures per hospital, and the frequency with which diagnostic procedures lead to stenting, displayed in Table 2 and Figure 2, all provide a sense of this demand heterogeneity.

Table 2: Market share variation across hospitals. The table reports summary statistics for the distribution of market share (% of all stents used) across hospitals. (Average shares do not add up to 100% because not all stents are used by all hospitals, as documented in the last column of the table.) The sample is restricted to September 2005 (middle of the sample in time) to isolate cross-sectional variation. There are N=54 hospitals sampled in this month, and BMS1-3 have exited the market.

brand	mean (%)	std. dev. (%)	std.dev./mean	min (%)	max (%)	N
BMS4	5	3	0.7	1	14	25
BMS5	3	2	0.6	1	7	23
BMS6	6	6	1.0	1	25	26
BMS7	4	5	1.1	1	25	39
BMS8	4	4	1.1	1	14	11
BMS9	8	8	1.0	1	32	47
DES1	43	30	0.7	1	88	54
DES2	41	30	0.7	2	93	54

Taking a closer look at the market share data also provides some preliminary evidence regarding the amount of vertical versus horizontal variation in demand across hospitals, which theory suggests will play an important role in determining the effects of competition under price discrimination versus uniform pricing. Regressing the September 2005 (to isolate cross-hospital variation) market shares (percent of diagnostic procedures that are treated with each stent) on stent dummy variables, and then on stent and hospital dummy variables, reveals that hospital effects explain only 12% of the within-stent variation in market shares. The remaining 88% is stent-hospital specific variation, suggesting more asymmetry (horizontal variation) than symmetry (vertical variation) in demand patterns across hospitals. This is an imperfect test with raw data, but it is a first piece of evidence that competition may be more intense under price discrimination than under

Figure 2: Distribution of procedure volumes across hospitals. All patients must have a diagnostic procedure to locate any blockages and detect their severity. The graph on the left shows the distribution of the average number of these procedures each hospital performs per month. The graph on the right shows the distribution of the average percentage of these procedures that result in a stenting intervention. The table below contains summary statistics for the two distributions.



	mean	std. dev.	min	median	max	N
Diagnostic angiographies (procedures/hospital-month)	283	185	58	232	934	96
Share of diagnostic angiographies resulting in stenting (%)	28	9	5	26	52	96

uniform pricing.

Prices are usually negotiated directly between each manufacturer and each hospital, and these negotiations are another potential source of the observed price variation. The typical contract is linear, specifying a price per unit for a given stent over the contract period, often one year.[10] Who is involved in the negotiation and the incentives they face differ across hospitals and manufacturers, and anecdotal evidence suggests that this could also be an important source of variation in the final price.

How much these forces influence price variation, and how they affect welfare with a change to uniform pricing, is ultimately an empirical question. Estimating the unobserved variables and disentangling their effects is the purpose of the rest of this paper.

2.4 Variation Over Time

While the cross-sectional variation in the data is what this paper is most interested in understanding, the identification strategy will rely on variation in prices and market shares over time for each stent-hospital combination. Table 3 summarizes this variation in the data. Prices change on average every 5 months, and while on average prices

[10]Some contracts could have discrete non-linearities, offering a lower price if the hospital uses that stent almost exclusively, say 80% of the time. While I do not observe the actual contracts, Appendix A shows that there is little if any evidence in the data for exclusivity playing a role in the observed price variation. However, my demand identification approach allows for this possibility.

decrease slightly over time, there is a great deal of variation in both the direction and size of price movements. For market shares, the average change is zero, but again there is a great deal of variation around the average.

Table 3: Price and market share variation over time. Summary statistics of changes over time for a given stent-hospital combination. Prices are conditional on a price change occurring. Market share is percentage of stents used.

variable	mean	std. dev.	min	max	N
change in price, $	-30	214	-1300	1150	2042
change in share, %	0	4.5	-66	46	10,098

3 Modeling Supply and Demand for Coronary Stents

The main goal of the this section is to estimate the parameters of a structural model that will distinguish among and quantify the various determinants of price variation across hospitals (demand, costs, competition, and bargaining abilities) and provide a "laboratory" in which to conduct policy experiments of changes that would limit the ability of device manufacturers to price discriminate. The model predicts the quantities of each stent used by each hospital and the prices negotiated for each stent by each manufacturer-hospital pair. The model derives those predictions in terms of a set of parameters that allow for heterogeneity across doctors/patients, hospitals, and time. Following Berry, Levinsohn, & Pakes (1995) and related literature, a generalized method-of-moments algorithm estimates these supply and demand parameters by matching the quantities and prices predicted by the model to the quantities and prices observed in the data. The main innovations in the estimation are: (1) find a source of variation to identify the demand curve and solve the simultaneity issue in demand estimation (when prices are negotiated); and (2) separately identify cost and bargaining ability parameters in the pricing model.

The agents in the model are the device manufacturers who supply the products, the doctors/patients whose decisions determine demand for those products, and the hospitals that negotiate prices with manufacturers. The model is a two-stage game with no information asymmetries:

Stage 1: Pricing Device manufacturers and hospitals contract on prices, taking expected future quantities into account.

Stage 2: Demand Given prices and choice sets, doctors decide on stent purchases as patients arrive at the hospital.

Because the first stage pricing equilibrium depends on expected demand, the discussion starts from the second stage and works backwards.

3.1 A Model of Demand for Coronary Stents

I model demand using a discrete choice random utility model of how doctors choose which stent to use for each patient. This approach has the benefit of intuitively matching the actual doctors' decision process, and it accommodates the fact that the choice sets of available stents vary across hospitals and over time. It also allows for very flexibly shaped demand curves and the direct computation of consumer surplus measures (Nevo 2000), both of which are critical in this analysis.

A "market" is a particular hospital, h, in a particular month, t. The hospital has contracted with a set of stent manufacturers for the set of stent models $j \in \mathcal{J}_{ht}$. Over the course of a month, patients $i = 1, ..., Q_{ht}$ arrive at the hospital to undergo a diagnostic procedure. The arrival of patients is considered exogenous to stent pricing, and thus hospitals are monopsonists of their own flow of potential stenting patients.[11] The doctor chooses a treatment for each patient to maximize the following indirect utility function:

$$\max_{j \in \mathcal{J}_{ht}} \qquad u_{ijht} = \delta_{jht} + \varepsilon_{ijht}, \tag{1}$$

where δ_{jht} is the mean quality of product j across all patient/doctor combinations (in hospital h and month t), and ε_{ijht} is a stochastic patient-specific quality component with distribution $f_{ht}(\varepsilon)$, representing characteristics of the specific patient/doctor combination i that make the patient an especially good candidate for a specific stent. In the spirit of Blomqvist (1991), this utility function can be thought of as a reduced form for how a doctor incorporates his own preferences, patient welfare, and hospital profitability into the treatment decision.

The set $\mathcal{J}_{ht}$ also includes a choice $j = 0$ for a treatment other than stenting, and I normalize $\delta_{0ht} = 0$ so that the utility for each stent is the utility relative to the next best non-stent treatment.

The mean utility of product j in hospital h in month t is given by

$$\delta_{jht} = \theta_{jh} - \theta^p p_{jht} + X_{jt}\theta^x + \xi_{jht}, \tag{2}$$

where θ_{jh} is the mean utility of product j in hospital h over the sample period; θ^p is the marginal disutility of price p_{jht} (in utils per dollar); X_{jt} is a matrix of month-DES

[11] This is consistent with the findings of Dafny (2005), which finds little evidence that hospitals compete at the diagnosis level; rather, that they instead compete in overall hospital quality.

interaction dummy variables starting in January 2006 to account for the scare over DES safety during this time; and ξ_{jht} are unobservable time fluctuations in hospital preferences for each stent model.

Including the θ_{jh} fixed effects is important, as doing so controls for persistent unobserved heterogeneity at the product-hospital level (and thus also at the product level and hospital level). This heterogeneity across hospitals comes from different average preferences of doctors due to different opinions regarding the clinical data for each product, different mixes of patients, and different reimbursement levels for stenting procedures.

However, because ξ_{jht} is an average across different doctors with different preferences and different patients with different characteristics, monthly variation occurs when the sample of patients varies, when the month's patients are allocated differently among the hospital's doctors, or when an individual doctor receives information that changes her preferences. Attrition and recruitment of new doctors over time could also lead to changes in these unobserved preferences at the hospital level. To capture this, I model ξ_{jht} as evolving according to a first-order autoregressive (AR(1)) process

$$\xi_{jht} = \rho\xi_{jht-1} + \widetilde{\xi}_{jht}, \tag{3}$$

where $\widetilde{\xi}_{jht}$ is the innovation in hospital preferences for product j at time t, and ρ measures the persistence (of the variation around the mean θ_{jh}) over time.[12]

Not all doctor/patient combinations at a given hospital in a given month are the same, and the model captures these differences in the doctor/patient-specific unobservable term, ε_{ijht}. The distribution $f_{ht}(\varepsilon)$ is an important component of the demand estimation because it directly affects the extent to which different products are substitutes for one another. I model $f_{ht}(\varepsilon)$ as a *mixture* of nested logit models:

$$\varepsilon_{ijht} = \epsilon_{ijht}^{stent} + (1-\sigma_{stent})\epsilon_{ijht}^{des} + (1-\sigma_{stent})(1-\sigma_{des})\epsilon_{ijht} + \lambda_{ijht}, \tag{4}$$

where the three ϵ terms are the random coefficients representation for a two-level "nested logit" model (as derived in Cardell (1998)), and λ represents the mixing distribution.

ϵ_{ijht}^{stent} is a random component common to all stents, modeling the fact that patients vary in how badly they need a stent versus an alternative treatment—as $\sigma_{stent} \in [0,1]$ approaches 1, there is less substitution between stents and alternatives. ϵ_{ijht}^{des} is a random component common to all DES, modeling the fact that some patients will be especially suited for a DES or BMS—as $\sigma_{des} \in [0,1]$ approaches 1, there is less substitution between

[12]Note that any drift component of this process is subsumed into θ_{jh}. There are well-known challenges in models where dynamic processes are combined with fixed effects (for a nice overview see Blundell and Bond 2000). Appendix **??** presents the specifications checks that led to this preferred demand specification.

DES and BMS.

ϵ_{ijht} and λ_{ijht} are random components specific to stent j, modeling the fact that some doctors may have very strong preferences for a particular stent for a particular patient. ϵ_{ijht} is the standard "logit" error term (extreme value type I normalized with mean zero and scale 1). The random mean shifter, λ_{ijht}, takes the value λ_{des} or λ_{bms} with probability ϕ_{jht} and zero otherwise. This allows the distribution of doctor/patient tastes for each stent to be *bimodal*, capturing the fact that a doctor may have a strong preference for a particular stent (Hastings (2008) and many papers in the marketing literature use a similar setup to characterize "brand loyalty"). Allowing for this possibility is critical because a bimodal distribution allows for a demand curve with multiple groups of consumers, each with similar willingness-to-pay, whereas a unimodal distribution does not; and these two situations have very different implications for pricing.

3.1.1 Market Shares and Demand Estimation

Given this demand structure, define the set of patients for whom a doctor chooses product j (in hospital-month ht) as $\mathcal{A}_{jht} := \{i | j = \arg\max_{k \in \mathcal{J}_{ht}} u_{ikht}\}$. Then expected market shares for each stent are given by the choice probability for each stent in each market:

$$s_{jht} = Pr[j = \arg\max_{k \in \mathcal{J}_{ht}} u_{ikht}] = \int_{\mathcal{A}_{jht}} f_{ht}(\varepsilon) d\varepsilon. \tag{5}$$

I estimate the demand for coronary stents by matching the observed market share data to the expected market shares predicted by the demand model, and using the contraction mapping from Berry, Levinsohn, & Pakes (1995) to invert this system of equations to obtain an equation that is linear in the parameters, data, and unobservable, ξ_{jht}. The econometric unobservable is then isolated by taking pseudo-differences (i.e., $\tilde{x} := x_t - \rho x_{t-1}$), yielding

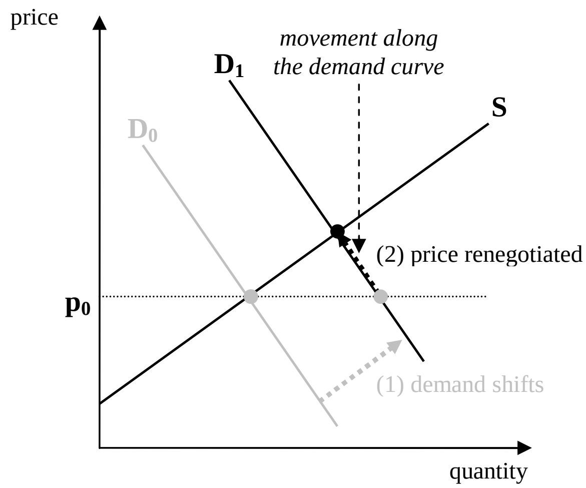
$$\widetilde{\xi}_{jht} = \tilde{\delta}_j(s_{ht}; \sigma, \lambda, \phi) - \theta_{jh}(1-\rho) + \theta^p \tilde{p}_{jht} - \tilde{X}_{jt}\theta^x. \tag{6}$$

which can then be interacted with a set of instrumental variables Z^d satisfying $E[\widetilde{\xi} | Z^d] = 0$ to estimate the demand parameters.

3.1.2 Demand Identification with Negotiated Prices

The economics of negotiated prices in long-term contracts introduce two new sources of identification for demand: (1) When prices are negotiated, bargaining ability becomes available as an additional supply shifter. (2) When prices are fixed in long-term contracts and demand shifts over time, the observed prices and quantities will be "out of equilibrium" until price is renegotiated. When price is renegotiated, the movement will be along the demand curve, identifying demand, as illustrated in Figure 3 below.

Figure 3: Fixed price contracts provide a new source of identification.



Along with these sources of exogenous variation, demand identification relies on a *timing assumption*: that price negotiations do not anticipate and take into account future changes in demand that are not already incorporated in current demand. This assumption seems reasonable in this context because any future development that is certain enough to be taken into account in pricing negotiations seems likely to already be incorporated into current demand. Failure of this assumption would require a situation where a device salesperson knows about a forthcoming study regarding a stent, convinces the hospital purchasing negotiator that this future study will increase future demand, but keeps this information from doctors so that it does not increase current demand.

Under this identifying assumption, if new prices are always negotiated at the beginning of a month, then realized demand is a response to this new price and any subsequent changes in demand, and there is no simultaneity problem in using contemporaneous price as its own instrument. However, I take a more conservative approach and construct a set of instrumental variables using one month lags to ensure that the instruments are uncorrelated with unobservable changes in demand over time. I instrument for the price of each stent using: (1) lagged own price, which uses the economics of long-term contracts as a source of identifying variation; and (2) the lagged average price of other stents at the same hospital, which captures supply side variation over time in hospital bargaining ability (and also in competition as demand for other stents changes, similar in spirit to the Berry, Levinsohn, and Pakes (1995) instruments).

Similar to Lee (2009) and Sweeting (2009), these lagged values will be correlated with contemporaneous price if any of demand, cost, or bargaining ability evolve over time according to some imperfectly persistent process. Both demand and bargaining ability should do so in this application. Monthly variation in demand occurs due to changes in doctor preferences (as new studies are released and device salespeople spread the word) or doctor turnover within a hospital over time. Imperfectly persistent variation in bargaining abilities would result from changes over time in the individuals involved in bargaining for a given stent at a given hospital, changes in the incentives faced by the same individuals, or learning by the same individuals over time. Appendix C confirms that these instruments are strongly correlated with price.

The nonlinear parameters in the demand function—the mixture parameters $(\lambda_{bms}, \lambda_{des})$ and nested logit parameters $(\sigma_{stent}, \sigma_{des})$—are identified by nonlinearities in the demand curve and variations in the market share responses within stent type and versus the outside good. To capture the nonlinearities, I use a semi-parametric basis of the squares of the price instruments, lagged market shares, and their interaction. To capture the substitution patterns across groups, I use lagged logarithms of the within-stent and within-DES market shares (the standard nested logit instruments). Other regressors serve as their own instruments, as detailed in Appendix B.

3.1.3 Elasticities and Surplus Measures

The demand parameters enter the pricing model through expected quantities, elasticities, and hospital/doctor/patient surplus measures. The maintained assumption is that all of these measures can be obtained from the revealed preference estimates of the utility parameters for how doctors incorporate their own preferences, hospital preferences, and patient preferences in choosing a treatment for each patient. Further, I assume that these utility parameters are structural in the sense that they do not change with the changes in market structure considered in Section 5.

At the time of contracting, the exact set of patients that will show up at the hospital is uncertain. So expected quantities for any given price vector $\vec{p}_{ht} = \{p_{jht}\}_{j\in\mathcal{J}_{ht}}$ are anticipated via expected market shares by $q_{jht}(\vec{p}_{ht}) = s_{jht}(\vec{p}_{ht})Q_{ht}$. Price elasticities, $\frac{\partial q_{jht}}{\partial p_{kht}}\frac{p_{kht}}{q_{jht}}$ and hospital surplus, $\pi_{ht} = \sum_{j\in\mathcal{J}_{ht}}\int_{\mathcal{A}_{jht}}\frac{u_{ijht}}{\theta^p}d\varepsilon$ are similarly considered in expectation. The explicit equations for all three come from the distributional assumption on ε, and are thus a linear combination of the well-known equations for the nested logit, detailed in the estimation Appendix B.

Deriving expected quantities and elasticities in this way matches exactly with the modeling set up and reality in the stent market that the decision about how to treat each patient is made by the physician, and thus represents how that physician weights her own preferences, those of the patient, and those of the hospital. Extending this physician utility function to the hospital surplus measure that will enter pricing negotiations, though, is not an obvious step and warrants further discussion. The motivation behind this step—which implicitly says that doctors and administrators behave according to the same utility function in assessing the value of a given stent—can be best captured by a quote from an article on physician preference items in the Journal of Healthcare Contracting (November/December 2009, p.12). It reads, "In many cases, physicians—when given good data to work with—will work out supply chain issues amongst themselves in a way that pleases both the clinical and administrative sides of the house." The intuition behind this comes from the fact that, despite their different roles within the organization, in the end doctors and administrators care about many of the same things: patient health, doctor satisfaction, and hospital profitability.

What if the surplus function for administrators who negotiate prices is different than that of doctors who choose which stents to use (e.g. more price sensitive)? To the extent this is the case, it will be captured in the bargaining ability parameters in the pricing model presented in the next section. This introduces a slightly different interpretation for a high hospital bargaining ability. A high bargaining ability may result from the ability to drive a better deal with device manufacturers, or it may result from an administrators power to maintain and act upon a more price-sensitive view of the available stents than the doctors at that hospital.

3.2 Modeling Pricing with Competition and Bargaining

Prices are set in a model of bargaining in the presence of competition where each hospital negotiates with each manufacturer separately and simultaneously, with the outcome of each negotiation satisfying the bilateral Nash Bargaining solution (the weighted product of the manufacturer and hospital payoffs). The outcomes of these bilateral negotiations must be consistent with one another, forming a Nash Equilibrium in the sense that no party wants to renegotiate. Formally, prices are determined as a Nash Equilibrium of bilateral Nash Bargaining problems (first introduced in Horn and Wolinsky (1988)). Each bilateral price maximizes the Nash Product of manufacturer profits and hospital surplus, taking the other prices as given, solving

$$\max_{p_{jht}} \quad [q_{jht}(\vec{p}_{ht})(p_{jht} - c_{jht})]^{b_{jt}(h)} [\pi_{ht}(\vec{p}_{ht}) - d_{jht}]^{b_{ht}(j)} \qquad \forall j \in \mathcal{J}_{ht}, \tag{7}$$

where the parameters $b_{jt}(h), b_{ht}(j) \geq 0$ represent the bargaining ability of the manufacturer 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 manufacturer's disagreement payoff is zero by the assumptions that the hospital is a monopsonist, the manufacturer is not capacity constrained, and each hospital is small enough that any returns to scale in manufacturing are not affected by inclusion or exclusion from a single hospital. Here I write the model with each product negotiated separately, though it is possible to allow for multi-product manufacturers, as discussed in Appendix B.2.1.

A variation of this model has been used in prior empirical work by Crawford and Yurukoglu (2010), and many related models have been developed in theoretical work on bilateral negotiations with externalities (e.g. Stole & Zwiebel (1995); de Fontenay and Gans (2007)). This prior work includes detailed discussions on how this model "nests" the solutions to many other pricing models of interest. Of particular interest here are: when the hospital has zero bargaining ability ($b_{ht}(j) = 0, \forall j \in \mathcal{J}_{ht}$), manufacturers set prices in a Bertrand-Nash price equilibrium; and when a manufacturer has zero bargaining ability ($b_{jt}(h) = 0$), that manufacturer prices at cost. Also, different assumptions on the threat points, d_{jht}, correspond with different notions of bargaining. Here I follow Horn and Wolinsky (1988) and Crawford and Yurukoglu (2010), letting $d_{jht} := \pi_{ht}(\vec{p}_{ht}; \mathcal{J}_{ht} \setminus \{j\})$, where the parties assume that other contracts would not be renegotiated if they did not reach agreement.

The clearest way to understand the model is by taking the first-order conditions of (7), which yield the following pricing equation:

$$p_{jht} = c_{jht} + \frac{b_{jt}(h)}{b_{jt}(h) + b_{ht}(j)} \left[\underbrace{\left(1 + \frac{\partial q_{jht}}{\partial p_{jht}} \frac{p_{jht} - c_{jht}}{q_{jht}}\right)}_{\text{NTU adjustment}} \underbrace{\frac{\pi_{ht} - d_{jht}}{q_{jht}} + p_{jht} - c_{jht}}_{\text{“Added Value” of } j} \right], \tag{8}$$

which says that equilibrium prices are equal to cost plus a margin that is the manufacturer's bargaining ability relative to that of the hospital, multiplied by product j's "added value": the additional surplus created when the hospital contracts with product j versus when the hospital doesn't contract with product j. The portion of the added value appropriated by the hospital is adjusted by a term that takes into account that, in this non-transferable utility (NTU) game, a dollar increase in price also results in a decrease in quantity, so it does not transfer linearly into manufacturer profits.

The model requires that the term $\frac{\partial q_j}{\partial p_j} \frac{p_j - c_j}{q_j}$ lies in the interval $[-1, 0]$ (whereas the Bertrand-Nash case, where manufacturers set price, requires that it be exactly negative one).[13] This requirement means that, taking the prices in other negotiations as given, equilibrium prices must fall in the range where each manufacturer would prefer to increase price and the hospital would prefer to decrease price. Thus prices are always between marginal cost and the manufacturer's Bertrand-Nash best-response price.

[13] Algebraic manipulation of the pricing equation gives $p - c = \frac{b_j}{b_h}\left(1 + \frac{\partial q}{\partial p}\frac{p-c}{q}\right)\frac{\pi - d}{q}$. For price above cost and $d_{jh} = \pi_h(p; \mathcal{J} \setminus \{j\})$, all the components of this equation are positive, requiring that $1 + \frac{\partial q}{\partial p}\frac{p-c}{q} > 0$ as well.

Competition between substitutes enters this model in two ways: (1) via the hospital's disagreement point of not contracting with a given product; and (2) via the elasticities. The constraint of the hospital's disagreement point is reminiscent of solutions such as the Core, whereas the elasticities are directly related to standard models of price competition with differentiated products.[14] Via these two effects, more "competition," such as lower prices or greater substitutability among products, decreases both the added value and NTU adjustment terms, leaving a smaller piece of the pie for product j to capture. However, conditional on competition, the amount of value captured depends on bargaining via $\frac{b_j(h)}{b_j(h)+b_h(j)}$.

3.2.1 Pricing: Identification and Estimation

This section shows how costs and relative bargaining ability can be estimated at the buyer-supplier transaction (and thus firm) level using the demand estimates and the assumed model of bargaining and competition. The quantities to be estimated in the pricing equation (8) are costs, c_{jht}, and the relative bargaining ability ratio $\frac{b_{ht}(j)}{b_{jt}(h)}$. A full statistical model requires specifications for costs and bargaining in terms of data, parameters, and unobservables. Because the *full* distributions of c_{jht} and $\frac{b_{ht}(j)}{b_{jt}(h)}$ are not separately identified, one of these specifications must be entirely in terms of data and parameters—no unobservables (estimating both distributions without restriction would be analogous to attempting to estimate separate slope and intercept parameters for every observation in a linear regression).

I specify manufacturer marginal costs by

$$c_{jht} = \gamma_{bms}\mathbf{1}_{\{j=bms\}} + \gamma_{des}\mathbf{1}_{\{j=des\}}, \tag{9}$$

so that cost is determined entirely by whether the stent is a BMS or DES. Ideally, marginal costs would be stent-specific, but the data in this study is not able to identify a more flexible specification. This issue, and the robustness of the paper's results to cost estimates, are discussed at length in the results. I further assume that there are no unobservable determinants of costs. This assumption seems reasonable in this context because marginal costs of production and distribution are thought to be quite low and to vary little (if at all) for a given product across hospitals and time. Also, it allows me to estimate the full distribution of relative bargaining abilities, which I am specifically interested in for this study.

[14] Another way to see the connection between the two models is to look at the "elasticity pricing rule" generated by this model, $\frac{p_j - c_j}{p_j} = \frac{1}{-\frac{\partial q_j}{\partial p_j}\frac{p_j}{q_j} + \frac{b_h(j)}{b_j(h)}\frac{p}{(\pi_h - d_{jh})/q_j}}$, which is the same as the one from the Bertrand-Nash model when $b_h = 0$.

For relative bargaining ability, I specify

$$\frac{b_{jt}(h)}{b_{ht}(j)} = \beta_{jh}\nu_{jht}, \tag{10}$$

where β_{jh} measures the average relative bargaining ability of stent j to hospital h, capturing firm-specific features (such as hospital size) as well as allowing for different bargaining abilities for the same hospital across manufacturers and vice-versa. ν_{jht} is the econometric unobservable term that measures the extent to which bargaining outcomes in the data deviate from the outcomes suggested by the pair-specific bargaining abilities. ν_{jht} could represent the evolution of bargaining abilities over time (due to learning, changes in personnel, or changes in organizational incentives) or the possibility that bargaining outcomes are simply random (due to idiosyncratic events that might affect a particular negotiation). To the extent that bargaining outcomes vary a great deal over time, this specification will set $\beta_{jh} = 1$, and all variation will be due to the random unobservable term ν_{jht}.

3.2.2 Estimation of costs and bargaining abilities

Combining the cost and bargaining specifications with the pricing equation gives the statistical model

$$p_{jht} = \gamma_j + \beta_{jh}\nu_{jht}\left[\left(1 + \frac{\partial q_{jht}}{\partial p_{jht}}\frac{p_{jht} - \gamma_j}{q_{jht}}\right)\frac{\pi_{ht} - d_{jht}}{q_{jht}}\right], \tag{11}$$

and rearranging and taking logarithms so that the unobservable enters linearly gives

$$\ln\left(g(X^s_{jht};\gamma)\right) \quad = \quad \ln(\beta_{jh}) + \ln(\nu_{jht}), \tag{12}$$

where $g(X^s_{jht};\gamma) := \frac{p_{jht}-\gamma_j}{\left(1+\frac{\partial q_{jht}}{\partial p_{jht}}\frac{p_{jht}-\gamma_j}{q_{jht}}\right)\frac{\pi_{ht}-d_{jht}}{q_{jht}}}$ is the ratio of the amount of per-unit added value that goes to the hospital to the amount that goes to the manufacturer, adjusted by the elasticity term to account for NTU. Then the cost and bargaining parameters can be estimated based on the assumption $E[\ln(\nu)|Z^s] = 0$ for a set of instrumental variables Z^s. A detailed discussion of the estimation procedure can be found in Appendix B.

3.2.3 Pricing instruments and identification

The statistical model (11) based on the pricing equation clearly shows how the cost and bargaining ability parameters are identified by the fact that cost enters price as a constant term, while the relative bargaining abilities of the manufacturer-hospital pair are identified by the extent to which price changes as the added value of the stent changes.

The only potential problem is that added value can change in response to supply shifts as well as demand shifts because in this NTU game added value is a function of price (and thus bargaining abilities and costs). Higher bargaining ability can lead to a higher price and lower added value, biasing β_{jh} downwards. This is the supply side of the simultaneity problem.

While this is a potentially large problem in theory, I expect it to be small in this context for two reasons: First, allowing for stent-hospital specific bargaining parameters controls for fixed stent-hospital differences, meaning that the variation in unobserved bargaining ability is within stent-hospital and thus likely to be less of a problem than if variation across hospitals were used. Second, industry knowledge predicts (and demand estimates in the next section confirm) that prices play a relatively small role in driving substitution between products in this market, so the decrease in added value for an increase in bargaining ability (the mechanism that causes the potential bias) should be small.

Fortunately, the panel data and the fact that demand realizations are observed much more frequently than price renegotiations again offer an instrumental variables strategy to form predictions of the added value that are not correlated with a simultaneous change in bargaining ability. Similar to the functions of lagged shares on the demand side, lagged added value will be a valid instrument if any of cost, bargaining abilities, or demand evolve according to imperfectly persistent processes. The exogeneity of these instruments again relies on a timing assumption: that demand does not change in response to anticipated future changes in bargaining abilities.

4 Estimation Results

In this section, I discuss the estimates obtained via the framework developed in Section 3. I first present the demand and cost parameters and compare these to external data sources as a way to check that the model captures the industry in a realistic way. The results show that heterogeneity in demand and bargaining ability both play an important role in the observed price variation.

4.1 Demand Parameters

The demand parameters are a critical piece of the model because they give the distribution of preferences for each stent across hospitals and across doctors/patients within each hospital. These preferences relate directly to own and cross-elasticities, consumer surplus, and added value measures that enter the industry model and welfare analysis. This section discusses those quantities directly for the preferred demand model. Appendix C presents the utility parameter estimates themselves across several specifications used to determine the robustness and appropriateness of the one used here.

4.1.1 Demand elasticities

Table 4 shows the distributions of the elasticities for each type of stent across stents, hospitals, and months.[15] The own-elasticity estimates vary across particular stents and hospitals, but in all cases they are quite low, with means -0.32 for BMS and -0.52 for DES. The small elasticities do not appear to be due to a failure of the demand identification strategy. As detailed in Appendix C, the stent-hospital fixed effects, AR(1) disturbance, and instruments do an effective job of increasing the estimated price sensitivity compared to more naive approaches. Additionally, these small elasticities are consistent with two prominent facts in the stent market: (1) doctors are not very price-sensitive, and (2) prices are negotiated.

Table 4: Own- and cross-elasticity estimates. $\frac{\partial q_j}{\partial p_k}\frac{p_k}{q_j}$ distributions across hospitals, months, and stents of that type. Own-elasticities less than -1 are consistent with negotiated prices and inconsistent with suppliers setting prices to price-taking buyers.

price elasticity of q_j:	with respect to p_k:	mean	std. dev.	min	max
BMS	own	-0.32	0.07	-.70	-.09
		(0.03)	(0.01)	(0.07)	(0.01)
	other BMS	0.02	0.02	0.00	0.47
		(0.00)	(0.00)	(0.00)	(0.03)
	DES	0.12	0.14	0.00	1.70
		(0.01)	(0.01)	(0.00)	(0.06)
DES	own	-0.52	0.11	-.99	-.09
		(0.04)	(0.01)	(0.09)	(0.01)
	BMS	0.01	0.01	0.00	0.24
		(0.00)	(0.00)	(0.00)	(0.01)
	other DES	0.01	0.02	0.00	0.20
		(0.00)	(0.00)	(0.00)	(0.01)
Outside Alternative	BMS	0.01	0.01	0.00	0.12
		(0.00)	(0.00)	(0.00)	(0.01)
	DES	0.08	0.07	0.00	0.60
		(0.01)	(0.01)	(0.00)	(0.05)

Price enters the doctor's choice of treatment for a given patient because of pressure from administrators for doctors to take price into account where it is reasonable to do so.

[15] When interpreting the elasticity estimates, it is useful to keep in mind that on average, DES prices are about two and a half times (and shares about six times) those of BMS. For example, the largest cross-elasticity is for BMS with respect to DES price, but this is not because of increased substitution on this dimension. It is because quantities for BMS are small and prices for DES are large, so that a small percentage change in DES price tends to have a larger effect on BMS quantity in percentage terms.

The small elasticity estimates show that price does matter in treatment choice, but relatively little. This is consistent with how industry participants describe doctor behavior, especially for physician preference items like coronary stents. It is also consistent with the limited evidence from previous studies that also suggest physicians and hospitals are relatively insensitive to financial incentives: Gaynor et. al. (2004) find HMOs are able to reduce costs by 5% through physician incentive programs; and Dafny (2005) finds little evidence that hospitals adjust intensity or quality of care in response to changes in diagnosis-specific prices.

Another important point to keep in mind when interpreting the elasticity estimates is that, with negotiated prices, elasticities combine demand, competition, *and* bargaining abilities. In particular, as pointed out in the previous section, the bargaining model requires that $-1 \leq \frac{\partial q}{\partial p}\frac{p-c}{q} \leq 0$. Small elasticities go hand-in-hand with bargaining because prices are by construction lower than a price-setting supplier would set to a price-taking buyer. As a result, small elasticities could reflect low buyer price-sensitivity, low supplier bargaining ability, or a combination of both.

4.1.2 Willingness-to-pay, total surplus, and added value

The demand parameters also provide the distribution of willingness-to-pay across doctor/patient types, products, hospitals, and months via $wtp_{ijht} = u_{ijht}/\theta^p + p_{jht}$. The sum of willingness-to-pay across treated patients gives the total surplus generated by stenting procedures (relative to the next best treatment, which is usually to do nothing). The mean willingness-to-pay estimate for a stenting procedure is $6,521, which seems reasonable compared to the baseline reimbursement rate of $812 to doctors and the Huckman (2006) estimate of $4,900 for hospital marginal profits per angioplasty procedures. This provides another source of verification for the low price-sensitivity estimates, as greater price-sensitivity would imply lower willingness-to-pay.

Willingness-to-pay enters the bargaining model through a product's "added value"—the amount of extra value that is created when a hospital contracts with that product. Table 5 provides summary statistics for the distribution of expected added value (expectation over doctor/patient types) per unit, $\frac{\pi_h - d_{jh}}{q_{jh}} + p_{jh}$ (for now without subtracting manufacturer marginal costs), for each product across hospitals in September 2005. The added values are around three times as large as prices, indicating that hospitals (and doctors and patients) capture a large part of the added value. Further, the variation in added values is small enough that some variation in costs and/or bargaining abilities will be needed to explain the observed variation in prices.

Table 5: "Added value" estimates. $\frac{\pi_h - d_{jh}}{q_{jh}} + p_{jh}$ across hospitals for each stent. The sample is restricted to September 2005 (middle of the sample in time) to isolate cross-sectional variation. There are N=54 hospitals sampled in this month; BMS1-3 have exited the market.

	mean ($)	std. dev. ($)	min ($)	max ($)	N
BMS4	3916	265	3410	4345	25
	(425)	(30)	(40)	(48)	
BMS5	3681	232	3385	4325	23
	(410)	(17)	(39)	(43)	
BMS6	3874	323	3312	4770	26
	(426)	(38)	(36)	(49)	
BMS7	3872	286	3372	4798	39
	(417)	(32)	(38)	(53)	
BMS8	3811	461	3272	4860	11
	(405)	(27)	(36)	(43)	
BMS9	4163	441	3539	5840	47
	(441)	(44)	(38)	(57)	
DES1	6231	432	5386	7233	54
	(488)	(30)	(43)	(52)	
DES2	6262	382	5559	6973	54
	(489)	(37)	(43)	(56)	

4.2 Cost Estimates

The pricing equation specifies price as equal to cost plus a margin that is the bargaining ability of the manufacturer relative to the hospital times the elasticity-adjusted added value that is up for negotiation. The standard approach, assuming that suppliers set prices in a Bertrand-Nash Equilibrium to price-taking buyers, is equivalent to assuming a bargaining ability of zero for buyers. In that case, the implied cost for each observation is given from the demand estimates and supply assumptions. The analysis here relaxes the supply side assumptions to allow buyers to have bargaining abilities greater than zero. In this case, cost parameters and bargaining ability parameters are separately identified by the fact that cost is an intercept term in the pricing equation while relative bargaining ability is the slope term. The results indicate that allowing for bargaining is critical for obtaining reasonable cost estimates in the coronary stent market.

The first column in Table 6 presents the cost parameter estimates. The type-specific cost parameters—$34 for BMS and $1103 for DES—are close to the range that industry experts report in the second column of the same table.[16] However, the cost parameters

[16] Sources are interviews with current and former industry employees as well as Burns (2003). From a manufacturing perspective, a DES is essentially a BMS with a polymer-drug coating. The added cost of a DES is a result of the royalty paid to the drug patent owner (thought to be about $100 per stent); the added cost of the process of adding the drug coating; and the quality of the process of adding the drug coating. This last point can be particularly important, as some industry engineers quoted yields from the coating process as 15-20%, meaning that only about one in six DES passes quality inspection after the coating process. The variation in these ranges reflects different experts' assumptions regarding this and other aspects of what they think should enter marginal costs.

are fairly imprecisely estimated. This is because the stent-hospital-month added value terms range from three to seven thousand dollars, and prices for added values near zero are the ideal data to identify the cost parameters. Without such observations, the cost parameters are identified by extrapolations far from the region of the data, and small changes in the bargaining ability (slope) estimates can lead to larger changes in the cost (intercept) estimates.

Table 6: Cost estimates and comparison. The first column reports marginal cost estimates for the bargaining model used in this paper. Column two reports industry expert estimates for per-unit costs. The ranges reflect different experts' assumptions about what should enter "cost". Column three reports marginal cost estimates (mean and std. dev. across stent-hospital-months) implied by the model if manufacturers were assumed to set prices.

	bargaining model estimates, γ	industry expert estimates	assuming Bertrand, $b_h = 0$	
			mean	std. dev.
cost of BMS in $	34	100-400	-2211	547
	(79)		(471)	(75)
cost of DES in $	1103	400-1600	-2481	1325
	(286)		(660)	(174)

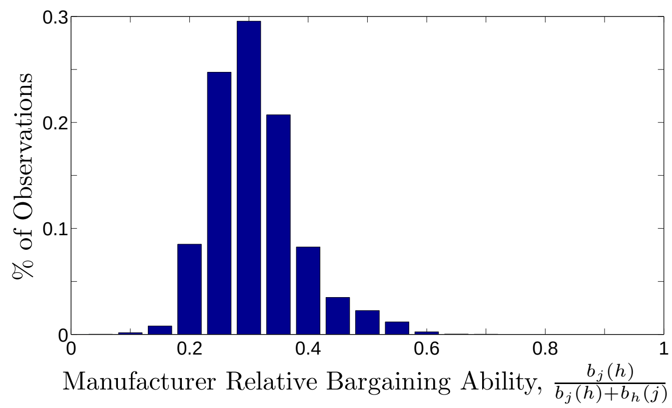
The third column in Table 6 gives the cost estimates implied by assuming that manufacturers set prices in a Bertrand-Nash Equilibrium, and these results point out two ways in which that model falls short. First, the mean cost estimates are unrealistically small because prices are negotiated, and to assume that manufacturers set price is equivalent to assuming that hospitals have zero bargaining ability, $b_h = 0$, which is not the case on average. Second, the variation in cost estimates across hospitals is unrealistically large because the Bertrand model fails to allow for variation in relative bargaining abilities, forcing the variation that cannot be explained by willingness-to-pay and competition into costs. Any model with fixed bargaining abilities will produce similarly unreasonable variation in costs.

Thus the model estimated in this paper, which allows for bargaining and heterogeneity in bargaining abilities, yields more reasonable cost estimates. Unfortunately, the cost estimates are imprecise because the observed added value measures are large. The "positive" aspect of this cost imprecision is that cost changes have only a small impact on subsequent estimates. Thus, as illustrated in Appendix C, the bargaining distribution and counterfactual estimates to come are robust to a variety of assumptions regarding costs. Any unobserved cost variation would have to be unrealistically large to materially affect the results.

4.3 Bargaining Distribution Estimates

Given demand and cost estimates, the estimated distribution of relative bargaining abilities, $\beta_{jh}\nu_{jht}$, is given by Equation 17. This distribution is easiest to interpret when each ratio is normalized to $\frac{b_{jt}(h)}{b_{jt}(h)+b_{ht}(j)} = \frac{\beta_{jh}\nu_{jht}}{\beta_{jh}\nu_{jht}+1}$, which takes the value 0 when the manufacturer prices at cost, and 1 when the manufacturer sets its Bertrand best-response price.

Figure 4: Distribution of bargaining ability of manufacturers relative to hospitals, $\frac{b_{jt}(h)}{b_{jt}(h)+b_{ht}(j)}$. Over all product-hospital-time observations. The measure takes the value 0 in the case where the hospital gets all the surplus (conditional on disagreement points) and the manufacturer prices at cost; and it takes the value 1 in the case where the manufacturer gets all the surplus, pricing at the highest price consistent with competition.



	mean	std. dev.	std. dev. / mean	min	max	N
$\frac{b_{jt}(h)}{b_{jt}(h)+b_{ht}(j)}$	0.33	0.07	0.22	0.08	0.71	10,098
	(0.04)	(0.01)	(0.02)	(0.02)	(0.07)	

Standard errors, clustered by hospital, in parentheses.

Figure 4 shows that both of these special cases are always rejected (the minimum observed is 0.08 and maximum 0.71). The mean of 0.33 indicates that, on average, the hospital is a more powerful negotiator. This is in addition to the fact that, as a monopsonist, the hospital extracts surplus via competition between the stents. However, with standard deviation of 0.07, there is significant variation around this mean. Grennan (2011) uses the model and panel data structure of the data to further explore this bargaining ability variation. Importantly for this study, the panel data allows for a regression of $\ln(\beta_{jh}\nu_{jht})$ on manufacturer and hospital dummy variables, and the coefficients on each firm dummy variable (β_j, β_h) provide a measure of the average bargaining ability of each firm across bargaining partners and over time. These firm-specific bargaining abilities are useful in calculating the expected prices under Group Purchasing Organizations and mergers in Section 5.

5 The Welfare Effects of More Uniform Pricing

The results in the previous Section indicate that the observed price variation across hospitals for a given stent comes from variation in both demand and bargaining abilities. Both of these sources of heterogeneity also play an important role in this Section, which examines several counterfactual scenarios with more uniform pricing, including: uniform prices set by manufacturers (a potential outcome of transparency reforms), centrally negotiated pricing for all hospitals (via GPOs or government purchasing), and negotiated prices at the level of merged hospital systems. The analysis makes clear that the details of how more uniform prices are implemented matter a great deal for whether or not prices for stents would rise or fall. Two particularly important forces that play a role in all cases are the effect of a move to more uniform prices on: (1) the intensity of competition, and (2) whether buyers are able to negotiate, and if so, at what bargaining ability.

The effect of imposing uniform pricing on the intensity of competition is closely related to what the price discrimination literature calls "best-response symmetry/asymmetry" (Corts 1998). If demand across hospitals for the different stents is symmetric in the sense that all stents prefer to set a higher price to the same hospitals (e.g., because compared to alternative treatments, these hospitals value *all* stents more than other hospitals), then a move to uniform pricing will tend to intensify competition (Holmes 1989; Stole 2007). On the other hand, if demand across hospitals is asymmetric in the sense that some hospitals prefer one stent while other hospitals prefer another (and thus different stents want to set high prices in different hospitals), then a move to uniform pricing will tend to soften competition as stent suppliers retreat to their more captive markets (Corts 1998). The results in this Section suggest that the market for coronary stents exhibits more asymmetry that symmetry in demand across hospitals, leading to competition to soften and—holding all else equal—making hospitals worse off under any policy that imposes more uniform pricing.

However, one especially important factor that may not be held equal is the impact of a change to more uniform pricing on bargaining abilities. The results in this Section suggest that, in order to reduce stent prices, any change to more uniform pricing must also induce a (potentially large) increase in hospital bargaining ability.

The welfare effects of the various market interventions considered in the rest of this Section depend upon exactly how that intervention triggers changes to competition and/or bargaining ability. A straightforward imposition of uniform pricing (either by mandate or perhaps indirectly through transparency measures) would both soften competition and remove hospitals' ability to negotiate. More centralized purchasing, (either through government or private group purchasing organizations) would suffer from softened competition, but has the opportunity to make up for this through increased bargaining ability. Mergers introduce an interesting complementarity between bargaining ability and symmetry of demand—while the competitive effect encourages mergers between hospitals with more symmetric variation in demand, the return to symmetry is increasing in the bargaining ability of the merged hospital group.

5.1 Centralized Pricing: Competitive *and* Bargaining Effects

In all of the counterfactual scenarios, prices are set according to a Nash Equilibrium of Nash Bargaining problems, as before; however, now there is only one price for each stent across the set $\mathcal{H}$ all hospitals (or for mergers in the next section, a subset of hospitals), so product and hospital profits are aggregated over hospitals. This has an interpretation of the hospitals bargaining collectively with each manufacturer, and the outcomes of these negotiations forming an equilibrium with one another, solving:

$$\max_{p_j} \quad \left[\sum_{h\in\mathcal{H}} q_{jh}(p_j - c_j)\right]^{b_j} \left[\sum_{h\in\mathcal{H}} (\pi_h - d_{jh})\right]^{b_{\mathcal{H}}} \qquad \forall j \in \mathcal{J}, \tag{13}$$

where $b_{\mathcal{H}}$ is a bargaining parameter for all the hospitals collectively. Table 7 compares the aggregate outcomes from the current price discrimination regime to counterfactual predictions under uniform pricing for three different values of the hospital group bargaining ability—$b_{\mathcal{H}} = 0$, $\overline{\beta_h}$, and $\max(\beta_h)$. In all cases, manufacturer bargaining abilities are set to their estimated means versus all hospitals, $b_j = \beta_j$.

The most dramatic change occurs if hospitals are unable to bargain collectively ($b_{\mathcal{H}} = 0$). This could result from direct imposition, or more likely, as a result of efforts to increase price transparency. There has been an active yet inconclusive policy debate on transparency in device pricing, with much of Issue 27, 2008, of *Health Affairs* devoted to the topic. While there are theoretical discussions on both sides of this issue, to my knowledge this is the first related empirical analysis. If, as Armstrong (2006) suggests, it is exactly the lack of transparency that allows sellers to cut the "secret discounts" that lead to different hospitals paying different prices, then increasing transparency could provide manufacturers a mechanism to commit to take-it-or-leave-it uniform pricing.[17]

To the extent that price transparency would lead to this outcome, it would have exactly the opposite effect that policy-makers concerned with hospital costs are looking for. I estimate that a move to uniform pricing with price-taking hospitals would cause

[17] One could imagine transparency having effects other than the extreme case analyzed here. A full analysis of the effect of transparency or other mechanisms such as most-favored-nation clauses would require a model of how these variables influence bargaining ability as well as data to identify how much. Such an analysis is beyond the current theoretical frontier and also beyond the data available here.

Table 7: Effects of changing to uniform pricing. Equilibrium outcomes under the current negotiated price regime compared to those under uniform pricing for September 2005. Column 2 sets $b_{\mathcal{H}}$ to zero, the case where hospitals do not bargain collectively and manufacturers set prices. Column 3 sets bargaining ability of the group of hospitals, $b_{\mathcal{H}}$, to the mean of individual hospitals, $\overline{\beta_h}$, in order to isolate the change to competition. Column 4 sets $b_{\mathcal{H}}$ to the maximum estimated bargaining ability of any individual hospital.

	Current Regime	% change with Uniform Prices		
		$b_{\mathcal{H}} = 0$	$b_{\mathcal{H}} = \bar{\beta}_h$	$b_{\mathcal{H}} = \max(\beta_h)$
manufacturer profits ($M/hospital/year)	1.24	81	8	-15
		(27)	(1)	(3)
hospital surplus ($M/hospital/year)	4.32	-48	-1.4	7.2
	(0.58)	(2)	(0.3)	(0.5)
total surplus ($M/hospital/year)	5.56	-19	0.7	2.2
	(0.75)	(1)	(0.1)	(0.2)
total stentings (stents/hospital/year)	977	-43	-1.1	5.9
		(2)	(0.3)	(0.4)
mean BMS price ($/stent)	1016	207	1.7	-25
		(35)	(0.4)	(1.6)
mean DES price ($/stent)	2509	114	1.7	-14
		(14)	(0.7)	(0.9)

Standard errors, clustered by hospital, in parentheses.

prices and manufacturer profits to approximately double; hospital surplus to decrease by 48% (profits 160%);[18] and total surplus to decrease by 19%. This large predicted price increase results from the fact that doctor/patient/hospital demand is estimated to be rather insensitive to price, and this counterfactual takes aways hospitals' ability to negotiate price. Prices at more than double the observed level are well outside the observed range of data (in particular, the equilibrium between administrators and doctors that induces doctor price sensitivity could be very different here), so these exact numbers should be taken with some skepticism. However, the robust takeaway is that any policy that removes the hospitals' power to negotiate would be bad news for hospitals.

5.1.1 More Uniform Prices Means Less Competition

The $b_{\mathcal{H}} = 0$ case is an extreme one in that it forces hospitals to become price-takers. In contrast, many implemented and proposed interventions in healthcare purchasing involve more centralized pricing that enforces uniform prices across large groups of hospitals, but also create a central purchasing authority that is able to negotiate on behalf of the "merged" group. In these cases with centralized negotiations, the results are more nuanced. Because there is little substitution to alternative treatments due to moderate

[18] Using detailed accounting data for hospitals in New York state, Huckman (2006) finds that marginal profits for angioplasty are on average 30% of revenues. I use this number to get ballpark estimates for the change in hospital profits implied by the surplus changes predicted by my model.

changes in stent prices, the effects on the total number of stentings and total welfare are small. As a result, the interesting changes are in the way the surplus is split between the device manufacturers and hospitals, and these changes are driven by a combination of the competitive and bargaining effects.

The results when hospitals bargain collectively at the mean bargaining ability of all the hospitals, $b_{\mathcal{H}} = \overline{\beta_h}$, isolate the competitive effect and show how competition softens under uniform pricing. Prices increase by 2% on average; manufacturer profits increase by 8%; and hospital surplus decreases by 1.4% (profits 5%).[19]

This competitive effect is consistent with the theoretical results on best-response asymmetry (Corts 1998) as well as the reduced-form evidence in Section 2 regarding the amount of asymmetry across hospitals in the market share data. It is also consistent with related studies in the gasoline (Hastings 2008) and coffee markets (Villas-Boas 2009) which also finds that prices increase with a change to non-discrimination. The hospital merger experiments in Section 5.2 explore this competitive effect in greater detail, using variation in the amount of symmetry among groups of merging hospitals to quantify the relationship between symmetry and post-merger hospital profits. Before exploring the competitive effect further, though, the last column of Table 7 sheds light on a feature that has not been noted before: the effect of bargaining ability on a change to more uniform pricing.

5.1.2 The Bargaining Effect: Post-"Merger" Bargaining Ability Matters

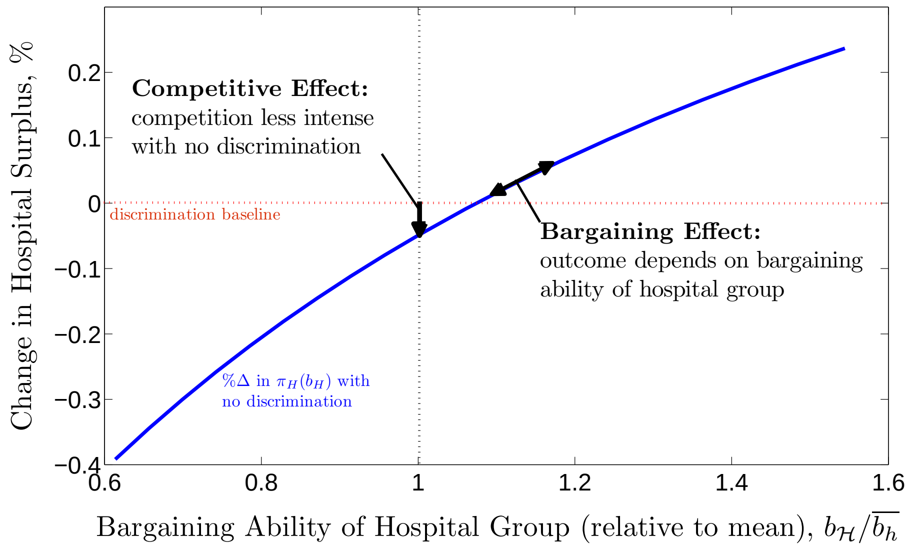
The competitive effect of merging demand across hospitals with asymmetric preferences works to raise prices, but the final price in any centralized purchasing scheme will depend on the bargaining ability of the "merged" group of hospitals. Allowing the group to have the maximum estimated bargaining ability across all hospitals, $b_{\mathcal{H}} = \max(\beta_h)$, is enough to overcome the competitive disadvantage. In this case, prices and manufacturers' profits fall by 14% and 15%; and hospital surplus increases by 7.2% (profits 24%).

Figure 5 provides a more precise perspective on the competitive and bargaining effects. The group of hospitals would need a bargaining ability more than 7% larger than the average hospital (or above the 70^{th} percentile of all hospitals) in order to overcome the disadvantage due to softer competition. Below this, hospitals would be worse off with group purchasing; above this, better off. The fact that only 30% of hospitals have

[19] Setting the group bargaining ability to the average across hospitals is not a perfect way to isolate the change due to competition because there are still two changes. A cleaner measure is to do the change in two steps: First, let all hospitals negotiate their own prices, but with their bargaining abilities fixed at the average; and second, have them negotiate as a group. The difference between the results in steps one and two isolates the true competitive effect. When I computed this, I found that the pure competitive effect accounts for over 90% of the change in prices.

such a high bargaining ability speaks to how difficult it might be to obtain.

Figure 5: Competitive and bargaining effects. The vertical axis is the percent change in hospital profits, and the horizontal axis is the bargaining ability of the hospital group as a ratio of the mean hospital bargaining ability. The upward sloping curve shows the relationship between the predicted hospital profits under uniform pricing and hospital bargaining ability.



The importance of this bargaining effect underscores how thinking about heterogeneity in bargaining abilities is important not only for understanding the prices negotiated by individual hospitals, but also for calculating expected outcomes under more uniform pricing. Looking back to the previously conjectured sources of bargaining abilities in the coronary stent market offers some guidance on how to think about the issue, but no solid prediction. To the extent that bargaining ability reflects actual negotiating skill of the individual purchasing administrator or organizational incentive system in which that individual operates, it might stand to reason that the best individuals and practices could be employed by a centralized purchasing group, leading to higher bargaining ability. On the other hand, to the extent that a large purchasing group might involve more bureaucracy and less influence with physicians, then bargaining ability might decrease. Unfortunately, the data is not available to directly address these effects in this study.

There are, however, external sources that provide some indication of the direction the combined competitive and bargaining effects take when large centralized purchasing groups are created. Looking at the data in Spain, the EU country with the most centralized purchasing system, shows a low coefficient of variation of 0.06 but a high (relative to other EU countries) mean of $2313 for DES2 across hospitals. Germany, which by contrast has a mostly decentralized purchasing system, shows a higher coefficient of variation of 0.16 and a lower mean of $1649 for the same stent in the same month. While this evidence is not systematic, it does show that more centralization in purchasing is not necessarily accompanied by enough bargaining ability to drive down prices relative to a decentralized system. Similar evidence exists for the U.S. in the fact that hospital group purchasing organizations (GPOs) play little to no meaningful role in the markets for coronary stents and other "physician preference items" (Burns and Lee 2008). The analysis here offers an explanation for this: GPOs are unable to achieve enough of an increase in bargaining ability to overcome the competitive disadvantage created by aggregating demand across hospitals with asymmetric demand. Thus GPOs are not able to provide value when it comes to physician preference items, where different doctors have brand loyalties to different manufacturers.

5.2 Hospital Mergers: Quantifying The Role of (A)symmetry

The results thus far are consistent with theory that predicts more asymmetry softens competition under uniform pricing because manufacturers to retreat to their captive markets. However, in real-world empirical settings, there is no such thing as complete symmetry or asymmetry, only some measure of the extent of one versus the other. Better understanding and quantifying this effect becomes especially important for thinking about hospital mergers because mergers may vary in the extent to which the merging hospitals exhibit (a)symmetry in their demand. This section develops a measure of demand symmetry among a group of buyers and quantifies the role of more or less symmetry in the context of hospital mergers into multi-hospital systems.

Of the 5,008 registered U.S. community hospitals, 2,921 are part of a multi-hospital system, with an average of seven hospitals per system.[20] The argument in favor of hospital mergers into systems often includes arguments for reducing costs, but the evidence regarding whether or not they do so has been mixed (see, e.g. Dranove and Lindrooth (2003) and the literature cited therein). In particular, there has been especially little evidence for (or against) the assertion that mergers lower input costs by increasing buyer market power. This Section provides evidence regarding the conditions under which hospital mergers might lower prices for coronary stents.

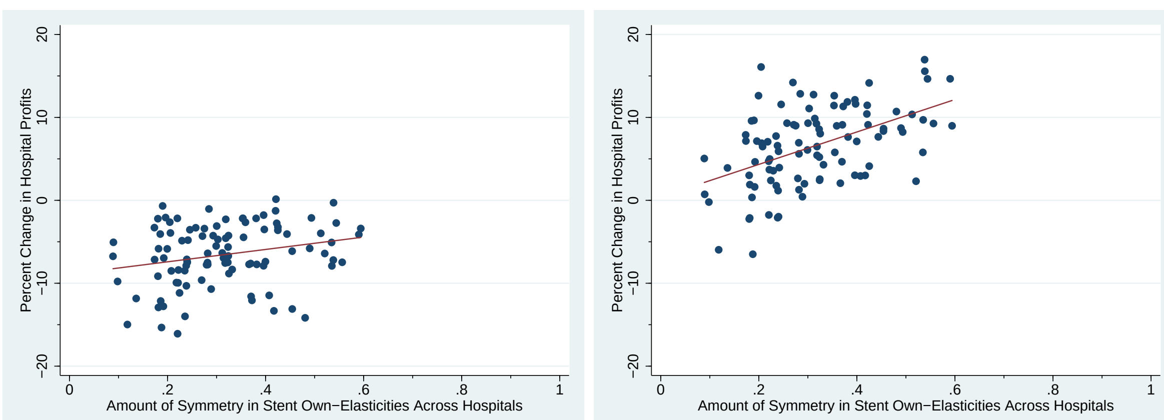
I examine this question by simulating 100 different mergers between groups of seven hospitals drawn randomly from the data set. Because the randomly selected groups of hospitals differ in their amount of symmetry in demand, these merger experiments provide a context in which to look at the impact of symmetry on the degree to which competition changes under uniform pricing. I measure symmetry among a group of

[20] http://www.aha.org/aha/resource-center/Statistics-and-Studies/fast-facts.html

hospitals by taking the across-hospital, within-stent variation in stent own-elasticities ($\eta_{jh} := \frac{\partial q_{jh}}{\partial p_{jh}} \frac{p_{jh}}{q_{jh}}$) explained by hospital dummy variables divided by the total stent-hospital variation, $Symmetry := \frac{Var(\hat{\eta}_{jh}(jFE,hFE))-Var(\hat{\eta}_{jh}(jFE))}{Var(\eta_{jh})-Var(\hat{\eta}_{jh}(jFE))}$. This measure is equal to 1 when hospitals are perfectly symmetric (purely vertically differentiated in their demand for the different stents), and equal to 0 when hospitals are perfectly asymmetric (purely horizontally differentiated). I simulate the new equilibrium prices and welfare measures after the mergers for two different assumptions on the post-merger bargaining abilities: the mean, $b_{\mathcal{H}} = \bar{\beta}_h$, and the max, $b_{\mathcal{H}} = \max(\beta_h)$, of the pre-merger bargaining abilities of the merging hospitals. The outcomes of these merger experiments, shown in Figure 6, both quantify the relative size of competitive and bargaining effects, and also highlight the complementarity between the two effects.

Figure 6: Competition softens more for mergers between hospitals with more asymmetric demand; this effect increases with bargaining ability. Results for 100 mergers of seven randomly selected hospitals. The two sets of results are for assumed post-merger bargaining ability equal to mean and maximum of the merging hospitals. The vertical axis shows the pre to post-merger change in hospital profits while the horizontal axis shows a measure of the amount of symmetry (vertical vs. horizontal differentiation) in demand elasticities ($\eta_{jh} := \frac{\partial q_{jh}}{\partial p_{jh}} \frac{p_{jh}}{q_{jh}}$) across the merging hospitals, $Symmetry := \frac{Var(\hat{\eta}_{jh}(jFE,hFE))-Var(\hat{\eta}_{jh}(jFE))}{Var(\eta_{jh})-Var(\hat{\eta}_{jh}(jFE))}$ (1 indicates perfect symmetry; 0 asymmetry).

(a) Merge with $b_{\mathcal{H}} = \bar{b}_h$ **(b)** Merge with $b_{\mathcal{H}} = \max(b_h)$



	Merge with $b_{\mathcal{H}} = b_h$	Merge with $b_{\mathcal{H}} = \max(b_h)$
Intercept (complete asymmetry)	-8.9	0.42
	(1.0)	(1.2)
Slope (as symmetry increases)	7.5	20
	(3.0)	(3.5)
R^2	0.06	0.24
% of Mergers where Hospital Profits Increase	1	92

Looking first at Panel (a)—the case where the merged hospitals have the mean bargaining ability of the merging hospitals (isolating the competitive effect)—the fitted line predicts that a merger between hospitals with perfect asymmetry in demand would result in a 8.9% decrease in hospital profits. Hospital profits increase with symmetry at a slope of 7.5, predicting that a merger between hospitals with perfect symmetry would still result in a decrease of 1.4% in hospital profits. With an R^2 of 0.06, the fitted line provides a noisy prediction of merger outcomes, so for very high levels of symmetry, the competitive effect is will often flip and work in favor of uniform pricing. Despite this somewhat encouraging extrapolation, the data suggest that high levels of symmetry are rare—across the 100 simulated hospital groups, the maximum symmetry measure is 0.59 (mean 0.31 and minimum 0.09). Thus for the highest symmetry actually observed, the competitive effect still softens competition substantially, with a predicted decrease of 4.5% in hospital profits.

Turning to Panel (b)—the case where the merged hospitals have the maximum bargaining ability of the merging hospitals—the fitted line predicts that a merger between hospitals with perfect asymmetry in demand would result in a slight increase in hospital profits of 0.4%. Thus the shift from mean to maximum bargaining ability was enough to erase the softening of competition for a merger of hospitals with very asymmetric preferences (though again the prediction is noisy, with an R^2 of 0.24). Beyond this upwards shift at low levels of symmetry, a perhaps more interesting result is the complementarity between symmetry and bargaining ability demonstrated by the dramatic increase in the slope of hospital profits with respect to symmetry to 20 (more than double the slope in the mean bargaining ability case). This increased slope predicts that mergers at the highest observed levels of symmetry will now result in a 12% increase in hospital profits.

A closer look at the theory helps to better understand these competitive and bargaining effects, and how they interact. Looking at the pricing equations under individually negotiated and uniform pricing (where the bar above a term denotes the quantity-weighted average over hospitals, e.g. $\overline{x_{jh}} := \sum_h \frac{q_{jh}}{\sum_h q_{jh}} x_{jh}$):

Non-Uniform:
$$p_{jh} = c_{jh} + \frac{b_j(h)}{b_j(h) + b_h(j)} \left[\left(1 + \frac{\partial q_{jh}}{\partial p_{jh}} \frac{p_{jh} - c_j}{q_{jh}}\right) \frac{\pi_h - d_{jh}}{q_{jh}} + p_{jh} - c_{jh} \right]; \tag{14}$$

Uniform:
$$p_j = \overline{c_{jh}} + \overline{\underbrace{\frac{b_j(\mathcal{H})}{b_j(\mathcal{H}) + b_{\mathcal{H}}(j)}}_{\text{bargaining effect}} \left[\underbrace{\left(1 + \overline{\frac{\partial q_{jh}}{\partial p_j} \frac{p_j - c_{jh}}{q_{jh}}}\right)}_{\text{demand/competitive effect}} \frac{\pi_h - d_{jh}}{q_{jh}} + p_j - c_{jh} \right]} \tag{15}$$

illustrates how the uniform case differs from the non-uniform case in two important ways.

First, under individually negotiated prices, what matters is the product-hospital elasticities, whereas under uniform pricing the relevant elasticity is a quantity-weighted average of these elasticities. Second, in the non-uniform case the product-hospital bargaining ratio is what matters, whereas under uniform pricing, the bargaining ratio is the same across all hospitals. The equations also show that the two forces interact multiplicatively in generating the results of a change to uniform pricing, giving rise to the increased role of symmetry when hospital group bargaining ability increases.

These results suggest that, similar to GPOs, hospital mergers need to increase bargaining ability if they are to decrease the prices hospitals pay for coronary stents. In addition, the more symmetry, the better. These insights provide some new ways to think about the mechanisms that may be behind the mixed results in research on the effect of hospital mergers on costs. Dranove and Lindrooth (2003) find that hospital mergers into systems in general have no statistically significant impact on costs, but that mergers between hospitals that subsequently do business under a single license and report unified financial records decrease costs by 14% on average. While at least some of the 14% gains of the "fully merging" cases is due to reduced headcount in redundant roles, this paper offers two additional explanations: (1) that hospitals are likely to more fully integrate post-merger when their doctors/patients/administrators exhibit less horizontally differentiated tastes; and (2) that hospitals who integrate more fully are more likely to share best practices and learn host to maximize post-merger bargaining ability.

6 Summary and Discussion

This paper combines new panel data on the prices and quantities transferred between medical device manufacturers and hospitals with a structural model of supply and demand to estimate the welfare effects of transparency, group purchasing, and hospital mergers in the coronary stent market. These interventions all restrict the ability of suppliers to sell at different prices to different hospitals. The major empirical challenge is that prices in the coronary stent market are negotiated (as they are in many business-to-business markets). I capture this using a model that generalizes the standard price-setting model to allow for bargaining, and I show how bargaining affects identification of both supply and demand parameters. The raw data and counterfactual estimates provide evidence that asymmetry in demand across hospitals leads to a softening of competition under more uniform pricing, consistent with the theory of price discrimination with oligopoly. However, final prices under non-discrimination also depend on the collective bargaining ability of the merged hospitals, which must be large to overcome the disadvantage of softened competition.

Taken together, these results suggest that moving towards more uniform pricing may be a difficult and indirect route towards lowering the prices hospitals pay for physician preference items such as coronary stents. This could be one reason why GPOs play such a small role in contracting for physician preference items and why hospital mergers often don't seem to reduce costs. If the goal is to lower the costs of medical technologies, a more fruitful approach might be to embrace the increased competition that comes with price variation and instead work directly on increasing bargaining ability and/or physician price sensitivity. Such an approach would be in line with the suggestion of Pauly and Burns (2009) for a focus on physician-administrator relations.

In addition to addressing the research question at hand, this paper suggests several avenues for future research. The quantitative results here suggest that both the nature of demand heterogeneity and bargaining ability—where firms end up within the range determined by costs, demand, and competition—matter. As more detailed data on vertical contracting relationships become available, it would be interesting to see the relative roles that demand (a)symmetry and bargaining ability play in other contexts.

Relatedly, while heterogeneity in bargaining abilities across firms plays an important role in both fitting the observed data and predicting outcomes under more uniform pricing, data limitations prevent a detailed examination of the determinants of bargaining ability. Anecdotal evidence from industry professionals suggests that there are economic forces such as human capital and organizational structure/incentives underlying these firm-level bargaining abilities. Better understanding the determinants of bargaining ability could lead to interesting links among internal firm activities and market outcomes. Pursuing this research topic would require detailed data related to the price negotiation process and individuals involved in addition to the detailed market data used here.

In the long run, market interventions that make prices more uniform, like anything that affects firm profitability, could impact market entry and exit on both sides of the market. In the medical device market, this is particularly important because the buyer side represents the availability of medical care and the supplier side represents the availability of new medical technologies. Future research that takes a step towards endogenizing the choices of who contracts with whom and market entry and exit would extend our ability to answer more dynamic research questions regarding medical technologies and our understanding of the economics of business-to-business markets in general.

References

Armstrong, Mark, "Recent Developments in the Economics of Price Discrimination," in Blundell, Newey, and Persson, eds., *Advances in Economics and Econometrics:*

Theory and Applications: Ninth World Congress, Cambridge University Press, 2006.

Berry, Steven T. and Philip A. Haile, "Identification of Discrete Choice Demand From Market Level Data," May 2009. Unpublished manuscript.

——, **James Levinsohn, and Ariel Pakes**, "Automobile Prices in Market Equilibrium," *Econometrica*, July 1995, *63* (4), 841–890.

Blomqvist, Ake, "The doctor as double agent: Information asymmetry, health insurance, and medical care," *Journal of Health Economics*, 1991, *10*, 411–432.

Burns, Lawton R. and J. Andrew Lee, "Hospital purchasing alliances: Utilization, services, and performance," *Health Care Management Review*, July-September 2008, pp. 203–215.

——, **ed.**, *The Business of Healthcare Innovation*, Cambridge, 2005.

Cardell, N. Scott, "Variance Components Structures for the Extreme-Value and Logistic Distributions with Applications to Models of Heterogeneity," *Econometric Theory*, 1997, *13*, 185–213.

Corts, Kenneth S., "Third-degree Price Discrimination in Oligopoly: All-Out Competition and Strategic Commitment," *RAND Journal of Economics*, 1998, *29*, 306–323.

Crawford, Greg and Ali Yurukoglu, "The Welfare Effects of Bundling in Multichannel Television," 2011. forthcoming in the American Economic Review.

Dafny, Leemore, "How Do Hospitals Respond to Price Changes?," *American Economic Review*, December 2005, *95(5)*, 1525–1541.

——, "Are Health Insurance Markets Competitive?," *American Economic Review*, September 2010, *100(4)*, 1399–1431.

de Fontenay, Catherine and Joshua Gans, "Bilateral Bargaining with Externalities," 2007. Unpublished manuscript.

Dranove, David and Richard Lindrooth, "Hospital Consolidation and Costs: Another Look at the Evidence," *Journal of Health Economics*, November 2003.

——, **Mark Satterthwaite, and Andrew Sfekas**, "Boundedly Rational Bargaining in Option Demand Markets: An Empirical Application." Unpublished manuscript.

Duggan, Mark and Fiona Scott Morton, "The Distortionary Effects of Government Procurement: Evidence from Medicaid Prescription Drug Purchasing," *Quarterly Journal of Economics*, February 2006, *121*, 1–31.

Gaynor, Martin, James Rebitzer, and Lowell Taylor, "Physician Incentives in Health Maintenance Organizations," *Journal of Political Economy*, August 2004, *112*, 915–931.

Grennan, Matthew, "Bargaining Ability and Competitive Advantage: Empirical Evidence from Medical Devices," 2011. Unpublished manuscript.

Hastings, Justine, "Wholesale Price Discrimination and Regulation: Implications for Retail Gasoline Prices," 2008. Unpublished manuscript.

Ho, Justin, Katherine Ho, and Julie Mortimer, "The Use of Full-line Forcing Contracts in the Video Rental Industry," 2011. forthcoming in the American Economic Review.

Ho, Katherine, "Insurer-Provider Networks in the Medical Care Market," *American Economic Review*, 2009, *99(1)*, 393–430.

Holmes, Thomas, "The Effects of Third-Degree Price Discrimination in Oligopoly," *American Economic Review*, March 1989, *79*, 244–250.

Horn, Henrick and Asher Wolinsky, "Bilateral Monopolies and Incentives for Merger," *RAND Journal of Economics*, 1988, *19*, 408–419.

Huckman, Robert, "Hospital integration and vertical consolidation: An analysis of acquisitions in New York State," *Journal of Health Economics*, 2006, *25*, 58–80.

Keehan, Sean P, Andrea M Sisko, Christopher J Truffer, and John A Poisal, "National Health Spending Projections Through 2020," *Health Affairs*, 2011, *30*, 1594–1605.

Kyle, Margaret and David Ridley, "Would Greater Transparency and Uniformity of Health Care Prices Benefit Poor Patients?," *Health Affairs*, 2007, (5), 1384–1391.

Lee, Robin S., "Vertical Integration and Exclusivity in Platform and Two-Sided Markets," 2009. Unpublished manuscript.

Myatt, David and Eric Rasmusen, "Posted Prices vs. Haggling: The Economics of Isoperfect Price Discrimination," April 2009. Unpublished Manuscript.

Nevo, Aviv, "A Practitioner's Guide to Estimating Random Coefficients Logit Models of Demand," *Journal of Economics & Management Strategy*, 2000, *9*, 513–548.

Pauly, Mark V. and Lawton R. Burns, "Price Transparency for Medical Devices," *Health Affairs*, 2008, *27*, 1544–1553.

Stole, Lars, *Handbook of Industrial Organization, Vol. 3* 2007.

Sweeting, Andrew, "Dynamic Product Repositioning in Differentiated Product Industries: The Case of Format Switching in the Commercial Radio Industry," 2007. NBER working paper.

Villas-Boas, Sofia B., "An Empirical Investigation of the Welfare Effects of Banning Wholesale Price Discrimination," *RAND Journal of Economics*, 2009, *40*, 20–46.

A Data Set Construction

The data set used in this paper is from Millennium Research Group's *Marketrack* survey of catheter labs, the source that major device manufacturers subscribe to for detailed market research. The goal of the survey is to provide an accurate picture of market shares and prices by U.S. region (Northeast, Midwest, South, West).[21] The key variables in the data are the price paid and quantity used for each stent in each hospital in each month. In addition, the hospitals report monthly totals for different procedures performed, such as diagnostic angiographies.

There are two main challenges in constructing a usable data set from the raw survey data. First, the survey was not as concerned with collecting price data as it was with collecting quantity data. Second, the survey was concerned with *usage* data, so whenever a stent is not used in a hospital-month that observation is missing (even if it is on the shelf and available for use). Table 8 illustrates how key sample summary statistics have remained stable as I took steps to "clean" the data set. More details are available in the Stata code used to execute these steps.

Table 8: Data set modifications

	Raw	Remove No p	Impute Some $q = 0$	Remove Sole	Final w/ Lags
# Diagnostic Procedures	272	271	273	303	304
	(13)	(19)	(19)	(23)	(23)
% Diagnostic Receive Stent	29	28	27	29	29
	(0.9)	(1.0)	(1.0)	(1.0)	(1.0)
BMS Price ($)	1011	1019	1026	1010	1009
	(10)	(15)	(15)	(15)	(15)
DES Price ($)	2522	2520	2540	2524	2513
	(11)	(17)	(18)	(21)	(21)
# Stent-Hospital-Months	21,035	10,669	14,245	11,301	10,098
# Hospital-Months	5867	2902	3038	2196	1973
# Hospitals	269	103	101	100	96

Standard errors clustered at the hospital level.

The table rows record the sample mean (and associated standard error) for: # of diagnostic angiographies per hospital-month, % of these diagnostic procedures that result in a stenting, BMS Price, and DES Price. It also records the total number of stent-hospital-month observations, number of hospital-month markets, and total number of hospitals in each sample. The table columns correspond to the different samples. The first column shows the results for the raw survey data with 21,035 observations across 269 hospitals. Many of the hospitals do not report price data, and removing these cases makes a substantially smaller sample of 10,669 observations across 103 hospitals

[21] See www.mrg.net for more details on the survey.

in column two. Despite the fact that observations are missing whenever $q_{jht} = 0$, there are cases where it is clear that a stent is little-used but present at a hospital. Whenever there are four or less months of no use surrounded by months of use for a stent, I impute the price for that observation. The data set is large, but small enough at this point to look over manually, and doing so reveals some glaring spots where data appears be misrecorded (for example, a hospital that usually performs 300 diagnostic procedure per month that suddenly performs 27), and I delete or impute these hospital-months as well. The result of these modifications is data set with 14,245 observations and 101 hospitals in column three.

There are two further modifications to the data set that result from a combination of data constraints and modeling choices. The first has to do with how to handle hospitals which still only use a single DES or BMS in a given month. There are three possible ways to deal with these cases: (1) leave them, implicitly assuming that no other stents were available in that hospital-month; (2) impute them, implicitly assuming that other stents were available at the imputed price, but no quantity was used; or (3) drop these hospital-months, assuming that these hospital-months are not systematically different from the rest of the sample. In this version of the paper, I choose option (3), dropping these observations. Leaving them as in (1) would not allow for modeling competition from the left out stents, which is unrealistic. Imputing them as in (2) would be an attractive solution if the price imputations were accurate. A previous version of this paper used the imputing route and obtained results qualitatively the same and quantitatively similar to those obtained here. However, there is always concern that the imputation procedure could drive results, especially those on the firm-specific determinants on prices in demand and bargaining abilities. Given these limitations, I prefer dropping the sole-source cases, as in (3), which does not rely on unrealistic assumptions or "creating data". One hospital and 2,944 observations are dropped in this step. As before, there are no statistically significant changes in the sample means in Table 8, though there is a 10% increase in the mean number of diagnostic procedures, consistent with the fact that $q = 0$ cases are more likely to occur in small hospitals for sampling reasons. Subsection A.1 explores in greater detail whether these dropped hospitals are indeed similar to the remaining sample, or if there is any evidence of these sole-sourcing instances being due to "exclusive dealing".

The final cut of the data occurs because the first observation for each stent-hospital pair is lost in taking the pseudo-differences for the demand unobservables, which are allowed to follow an AR(1) process. 1,203 observations and four hospitals are lost, with no statistically significant differences in the sample means, leaving the final sample used for estimation: an unbalanced panel of 10,098 stent-hospital-month observations over 96 hospitals for eleven stents from January 2004 through June 2007.

A.1 Potential Sole-Sourcing and Exclusivity

Because the data is recorded for stents *used* by a given hospital in a given month, it does not contain data on the set of stents available but not used. Further, the price data does not include any information besides price, such as exclusivity arrangements. Despite the fact that exclusive arrangements which impact prices paid are common in business-to-business markets, including many medical supplies, my understanding from talking with industry participants is that "exclusivity" did not play a major role in coronary stent pricing during the time of this study (2004-07). However, because the model used in this paper does not explicitly allow for strategic choices regarding "who contracts with whom", it is important to verify this omission empirically.

The analysis in this Section looks at the effects of exclusive (100% market share among similar type stents) and near-exclusive (over 80%) situations on prices paid for two stents: DES2 and BMS8.[22] The results indicate that neither exclusive nor nearly exclusive contracts seem to play a role in driving the observed price variation across hospitals.

Tables 9 and 10 show the results of several regressions of price on dummy variables for exclusivity for DES2 and BMS8. In each case, the first four columns present evidence regarding full exclusivity using the data set before the sole-sourcing cases are cut, and the next four for near exclusivity using the data set used in the paper. In each of these first two specifications are: (1) a regression of price on a dummy variable for exclusivity only (equivalent to a t-test of means between the two samples), and (2) the same regression with the addition of time dummy variables to account for the fact that prices decrease and observations of sole-sourcing increase over time, creating what could be a spurious effect. The next two specifications, (3) and (4), look at the same regressions, but using only within-hospital changes for the subsample of hospitals with both sole-sourcing and non-sole-sourcing months for that stent.

The point estimates for DES2 in Table 9 tell a story of exclusivity potentially being correlated with an average price decrease of $42-94, but these impacts going away once time dummies are included. This is consistent with the facts that prices decrease over time, and doctors may tend to settle on a preferred stent over time. It is also consistent with increased use of exclusive contracts over time, but even if that is the case, the remaining evidence suggests that this is not a systematically important phenomenon.

The point estimates are all very noisy, with none having a t-statistic greater than 1.4,

[22] These are chosen because they are the stents from each category where the most sole-sourcing is observed, suggesting that they would be the first place to look for any evidence of exclusivity. The results reported here are representative of those for other stents and for changing the threshold for near-exclusive to 70 and 90%, which are available upon request.

Table 9: Prices of DES2: Exclusivity and Near-exclusivity.

parameter	E1	E2	E3	E4	NE1	NE2	NE3	NE4
Exclusive, $s_{jht}\|_{g_j} = 1$	-42	-11	-94	28				
	(39)	(36)	(66)	(37)				
Nearly-exclusive, $s_{jht}\|_{g_j} > 0.8$					43	4	65	5
					(37)	(36)	(26)	(16)
Month Fixed Effects	-	Y	-	Y	-	Y	-	Y
Hospital Fixed Effects	-	-	Y	Y	-	-	Y	Y
N	2805	2805	742	742	1960	1960	1184	1184
# "Sole-source"	451	451	451	451	624	624	517	517
$N_{Hospitals}$	101	101	24	24	94	94	52	52
R^2	0.005	0.26	0.32	0.65	0.008	0.26	0.59	0.79

Standard errors clustered at the hospital level.

and the R^2 suggest that exclusivity does little to explain the price variation observed in the data. Relatedly, beyond the regression results regarding the two sample means, there is no discernible difference in the sample standard deviations either, at \$221 for sole-sourcers and \$225 for non. Combined with the further evidence that these sole-sourcing cases comprise only 16% of the hospital-month observations for DES2 (and this is the largest percentage observed for any stent), it seems difficult to make a case for an important role of full exclusivity. Results for near exclusivity are similar in every way except for the fact that the sample mean differences for the specifications without time dummy variables suggest that those with high market shares pay about \$43-65 *more* on average than others, which is more consistent with the standard problem of a positive correlation between price and market share as a result of unobserved quality than a story of exclusivity.

Table 10: Prices of BMS8: Exclusivity and Near-exclusivity.

parameter	E1	E2	E3	E4	NE1	NE2	NE3	NE4
Exclusive, $s_{jht}\|_{g_j} = 1$	15	52	-23	10				
	(41)	(41)	(16)	(28)				
Nearly-exclusive, $s_{jht}\|_{g_j} > 0.8$					-37	-8	-40	-0.8
					(40)	(43)	(16)	(17)
Month Fixed Effects	-	Y	-	Y	-	Y	-	Y
Hospital Fixed Effects	-	-	Y	Y	-	-	Y	Y
N	2260	2260	516	516	1597	1597	925	925
# "Sole-source"	168	168	130	130	173	173	173	173
$N_{Hospitals}$	89	89	21	21	82	82	39	39
R^2	0.0003	0.11	0.68	0.75	0.003	0.07	0.65	0.71

Standard errors clustered at the hospital level.

Looking to BMS8 and Table 10 shows similar small and noisy point estimates comparing sample means, little in sample standard deviation (\$193 for sole and \$221 for non), and infrequency of sole-sourcing in general (8% of observations).

As discussed above, not modeling exclusivity amounts to an assumption that whenever the data shows little or no use of a particular stent at a particular hospital, then this is because the doctors at that hospital do not prefer that stent, not because the stent was excluded for a strategic pricing reason. Despite the empirical checks here and discussions with industry insiders, there is no way to guarantee that no hospital has an exclusive agreement which affects pricing. To the extent that this occurs, those hospitals will show up as "high bargaining ability" hospitals in my analysis. This would be consistent with the broader interpretation (discussed now in Section 3.1.3, p17 and Section 5.1.2, p30) of my measure of bargaining ability as potentially capturing administrator power vis-a-vis doctors in addition to pure negotiating skill with manufacturers.

B Estimation Details

The estimation approach used in this paper makes some small departures from the well-known GMM algorithms developed in Berry, Levinsohn, and Pakes (1995) and related research. As such, I include a description of the algorithm here to aid in replication of this study or the use of such a model in other contexts with brand-loyalty in demand and/or negotiated prices. I use the identifying assumptions $E[\widetilde{\xi}' Z^d] = 0$ and $E[\hat{\widetilde{\nu}}' Z^s] = 0$ to construct a method-of-moments algorithm to separately estimate the demand $(\theta, \lambda, \sigma, \phi, \rho)$ and supply (γ, β) parameters . Although joint estimation would be more efficient, it would also constrain the demand parameters to be consistent with the bargaining model, while estimating the demand system separately allows the demand results to provide a check on the appropriate supply side model.

B.1 Demand Estimation Details

I estimate the demand for coronary stents following the procedure suggested in Berry (1994), matching the observed market share data to the expected market shares predicted by the demand model, and inverting this system of equations to obtain an equation that is linear in the parameters, data, and econometric unobservable, $\widetilde{\xi}_{jht}$, allowing the use of linear instrumental variables methods.

Following the customary notation in the literature on random coefficients demand estimation, it is useful to represent the portion of utility that is not patient/doctor-specific using the term δ_{jht}, so that $u_{ijht} = \delta_{jht} + \varepsilon_{ijht}$. Taking the expectation over the distribution of the patient/doctor unobservables, ε, as in (2) yields the market shares predicted by the model for each product, in each hospital, in each month (here each hospital-month is a separate "market"): $s_j(\delta_{ht};\sigma,\lambda,\phi)$. Where I use the vector notation $\delta_{ht} := (\delta_{1ht},...,\delta_{Jht})$ and $s_{ht} := (s_{1ht},...,s_{Jht})$.

Setting these predicted shares equal to the observed market shares yields a system of equations, $s_j(\delta_{ht};\sigma,\lambda,\phi) = s_{jht}$. Berry (1994) proves that there is a unique vector δ_{ht} that solves this system. Therefore, the system can be inverted to obtain the mean utility for a each product in each hospital in each month as a function of market shares and the parameters governing doctor/patient heterogeneity, $\delta_j(s_{ht};\sigma,\lambda,\phi)$. Under the assumed distribution of doctor/patient heterogeneity, $f(\varepsilon)$, the predicted market shares, $s_j(\delta_{ht};\sigma,\lambda,\phi)$, have a closed-form solution where each is a linear combination of the L "brand-loyal" mixture types, $s_j(\delta_{ht};\sigma,\lambda,\phi) = \sum_{l=1}^{L}\phi_{ht}^l s_j^l(\delta_{ht};\sigma,\lambda)$ and (note the equation below is written for a DES; for a BMS these two labels would switch places):

$$\begin{aligned}
s_j^l(\delta_{ht};\sigma,\lambda) &= s_{j|des}^l(\delta_{ht};\sigma,\lambda)s_{des|stents}^l(\delta_{ht};\sigma,\lambda)s_{stents}^l(\delta_{ht};\sigma,\lambda) \\
\text{where} & \\
s_{j|des}^l(\delta_{ht};\sigma,\lambda) &= \frac{I_{jht}^l}{\sum_{k\in des} I_{kht}^l} \\
s_{des|stents}^l(\delta_{ht};\sigma,\lambda) &= \frac{\left(\sum_{k\in des} I_{kht}^l\right)^{1-\sigma_{des}}}{\left(\sum_{k\in des} I_{kht}^l\right)^{1-\sigma_{des}} + \sum_{k\in bms} I_{kht}^l} \\
s_{stents}^l(\delta_{ht};\sigma,\lambda) &= \frac{\left[\left(\sum_{k\in des} I_{kht}^l\right)^{1-\sigma_{des}} + \sum_{k\in bms} I_{kht}^l\right]^{1-\sigma_{stent}}}{1+\left[\left(\sum_{k\in des} I_{kht}^l\right)^{1-\sigma_{des}} + \sum_{k\in bms} I_{kht}^l\right]^{1-\sigma_{stent}}} \\
\text{and where} & \\
I_{jht}^l &= \exp\left(\frac{\delta_{jht}+\lambda_{des}\mathbf{1}_{\{j=l\}}}{(1-\sigma_{stent})(1-\sigma_{des})}\right)
\end{aligned}$$

Because shares take a closed form, no simulation is necessary. However, the inverse, $\delta_j(s_{ht};\sigma,\lambda,\phi)$, must be solved numerically, using the contraction mapping from Berry, Levinsohn, & Pakes (1995) (modified slightly because the i.i.d. logit error term is scaled down by $(1-\sigma_{stent})(1-\sigma_{des})$).

Setting $\delta_j(s_{ht};\sigma,\lambda,\phi) = \delta_{jht}$ results in a model that is linear in the data and parameters, which can be solved for the econometric unobservables by taking pseudo-differences (i.e., $\tilde{x} := x_t - \rho x_{t-1}$), yielding

$$\widetilde{\xi}_{jht} = \tilde{\delta}_j(s_{ht};\sigma,\lambda,\phi) - \theta_{jh}(1-\rho) + \theta^p\tilde{p}_{jht} - \tilde{X}_{jt}\theta^x. \tag{16}$$

I then use the Price and Storn (2005) *Differential Evolution* global optimization algorithm to find the parameters that minimize the GMM criterion $\widetilde{\xi}'Z^d(Z^{d\prime}Z^d)^{-1}Z^{d\prime}\widetilde{\xi}$, subject to the parameter constraints implied by the model: $\theta^p \geq 0$; $\lambda,\sigma \leq 1$; $\rho \in [0,1]$.

The instruments used are

$$\begin{aligned} Z^d_{jht} \;=\; & \Big[\delta_{jht-1} \quad p_{jht-1} \quad \textstyle\sum_{k\neq j} p_{kht-1}/K_{ht-1} \quad \ln(s_{jht-1|stents}) \quad \ln(s_{jht-1|des}) \\ & p^2_{jht-1} \quad \left(\textstyle\sum_{k\neq j} p_{kht-1}/K_{ht-1}\right)^2 \quad s_{jht-1}p_{jht-1} \quad s_{jht-1}\textstyle\sum_{k\neq j} p_{kht-1}/K_{ht-1} \quad s^2_{jht-1}\Big]. \end{aligned}$$

I simplify the computational burden of estimation dramatically in two ways. First, I fix the probability, ϕ_{jht}, of each stent-specific shock λ_{ijht} taking the value λ_{bms} or λ_{des} (as opposed to zero) to be equal to the market share of that stent among the stents actually implanted in each hospital-month, $s_{jht|_{j=stent}}$. Although, in principle, the full distribution of ϕ_{jht} could be estimated, this introduces a large number of nonlinear parameters to an already difficult nonlinear minimization problem and asks a lot of the data, which are already being pushed to the limit with the stent-hospital fixed effects and AR(1) process. Note also that fixing the probabilities equal to market shares is not really an assumption when either $\lambda = 0$ or $\lambda >> 0$ (with the latter being the case here). Fixing the probabilities has no effect if the best-fit model is unimodal ($\lambda = 0$); and as $\lambda \to \infty$, the probability that a doctor who prefers stent j (in the sense that $\lambda_{ij} = \lambda$) chooses stent k goes to zero, so the probabilities converge to the market shares of each stent.

Also, conditional on values for the parameters $(\theta^p, \lambda, \sigma, \rho)$, estimation of (θ_{jh}, θ^x) is a linear regression problem, and their estimators must satisfy the first-order conditions for that linear regression. Thus instead of searching over (θ_{jh}, θ^x), I "concentrate out" these parameters, replacing them by their estimators as functions of $(\theta^p, \lambda, \sigma, \rho)$.

B.2 Supply Estimation Details

With demand estimated, I then estimate the supply parameters by finding the parameters that minimize the GMM criterion $\ln(\nu)' Z^s (Z^{s\prime} Z^s)^{-1} Z^{s\prime} \ln(\nu)$, subject to the demand parameter estimates from the first stage and the parameter constraints implied by the model: $\beta > 0$; $c_{jht} \in [0, p_{jht}]$; and $-1 \geq \left(1 + \frac{\partial q_{jht}}{\partial p_{jht}} \frac{p_{jht}-\gamma_j}{q_{jht}}\right) \geq 0$.

The supply unobservable is given by

$$\ln(\nu_{jht}) \;=\; \ln\left(g(X^s_{jht};\gamma)\right) - \ln(\beta_{jh}), \tag{17}$$

where $g(X^s_{jht};\gamma) := \frac{p_{jht}-\gamma_j}{\left(1+\frac{\partial q_{jht}}{\partial p_{jht}}\frac{p_{jht}-\gamma_j}{q_{jht}}\right)\frac{\pi_{ht}-d_{jht}}{q_{jht}}}$ is the ratio of the amount of per-unit added value that goes to the hospital to the amount that goes to the manufacturer, adjusted by the elasticity term to account for NTU.

The elasticities and added value terms are obtained from the demand estimates. The mixture of nested logits allows for closed form solutions, which dramatically speeds up estimation relative to cases when they must be simulated (e.g. normally distributed random coefficients). The elasticities are given by $\frac{\partial q_{jht}}{\partial p_{kht}}\frac{p_{kht}}{q_{jht}} = \sum_{l=1}^{L}\phi_{ht}^{l}\frac{\partial q_{jht}^{l}}{\partial p_{kht}}\frac{p_{kht}}{q_{jht}}$ where (suppressing the hospital and time subscripts):

$$\frac{\partial q_j^l}{\partial p_k} = |\theta^p| q_j \left(s_k + s_k|_{stent}\frac{\sigma_{stent}\mathbf{1}_{\{j,k\in stent\}}}{1-\sigma_{stent}} + s_k|_{des}\frac{\sigma_{des}\mathbf{1}_{\{j,k\in des\}}}{(1-\sigma_{des})(1-\sigma_{stent})} - \frac{\mathbf{1}_{\{j=k\}}}{(1-\sigma_{des})(1-\sigma_{stent})}\right)$$

and the hospital surplus is given by $\pi_{ht} = \sum_{l=1}^{L}\phi_{ht}^{l}\pi_{ht}^{l}$ where:

$$\pi_{ht}^{l} = \frac{1}{|\theta^p|}\ln\left(1+\left[\left(\sum_{j=des} e^{\frac{\delta_{jht}+\lambda_{des}\mathbf{1}_{\{j=l\}}}{(1-\sigma_{stent})(1-\sigma_{des})}}\right)^{1-\sigma_{des}} + \sum_{j=bms} e^{\frac{\delta_{jht}+\lambda_{bms}\mathbf{1}_{\{j=l\}}}{(1-\sigma_{stent})(1-\sigma_{des})}}\right]^{1-\sigma_{stent}}\right). \tag{18}$$

The hospital disagreement point d_{jht} for each stent is calculated as the hospital surplus when that stent is removed from the choice set and prices of other stents remain the same (this is the "Nash" or "passive beliefs" assumption on disagreement points used in much of the bargaining with externalities literature, including the original Horn and Wolinsky (1989) and recent empirical work by Crawford and Yurukoglu (2011)).

The instruments used are the first derivatives of the unobservables with respect to the parameters, lagged by one month:

$$Z_{jht}^{s} = \begin{bmatrix}\mathbf{1}_{\{bms\}}\frac{p_{jht-1}}{1+\frac{\partial q_{jht-1}}{\partial p_{jht-1}}\frac{p_{jht-1}}{q_{jht-1}}} & \mathbf{1}_{\{des\}}\frac{p_{jht-1}}{1+\frac{\partial q_{jht-1}}{\partial p_{jht-1}}\frac{p_{jht-1}}{q_{jht-1}}}\end{bmatrix}$$

The search is only over the cost parameters because again, instead of searching over (β_{jh}), I "concentrate out" these parameters by taking the "within" transformation, subtracting stent-hospital means.

B.2.1 Multi-product manufacturers

The model in the paper treats pricing for each product independently, but optimal behavior for a multi-product device manufacturer would be to take into account the externalities between its products. Let $m \in \mathcal{M}$ denote the manufacturers contracting with hospital h, with m_j denoting the manufacturer of product j. The new pricing equilibrium must then solve

$$\max_{\{p_j\}_{m_j=m}} \; [\pi_m(p)]^{b_m}\,[\pi_h(p) - d_{mh}]^{b_h} \qquad \forall m \in \mathcal{M}, \tag{19}$$

where $\pi_m = \sum_{j \text{ s.t. } m_j=m}\pi_j$ is the total profits to manufacturer m and now negotiation occurs at the manufacturer level, so the relevant bargaining ability parameter is b_m, and the relevant outside option is d_{mh}. Note this has two effects: (1) the profit function of the manufacturer now takes into account externalities between its product's prices and (2) the hospital's outside option now reflects failure of bargaining with *all* of the manufacturer's products. This second reason is why I choose not to use the multi-product manufacturer setup in this paper—several hospitals in the data use a subset of a given manufacturers' products. Combined with the low cross-elasticities, which makes externalities between products less of a concern, the stent-specific pricing model seems more appropriate for this application.

The first order conditions of this optimization problem now yield a vector of equations that relate the profits of a manufacturer to its "added value" via

$$\pi_m = \frac{b_m}{b_m + b_h} \left[\underbrace{\left(-\frac{\partial \pi_m / \partial p_j}{\partial \pi_h / \partial p_j} \right)}_{\text{NTU adjustment}} \underbrace{(\pi_h - d_{mh}) + \pi_m}_{\text{“Added Value” of } m} \right] \qquad \forall j \text{ s.t. } m_j = m. \tag{20}$$

Note that the NTU adjustment here now changes the requirement that $\frac{\partial q_j}{\partial p_j} \frac{p_j - c_j}{q_j} \in [-1, 0]$ by taking the cross partials into account, making the requirement $\frac{\partial q_j}{\partial p_j} \frac{p_j - c_j}{q_j} + \sum_{k \neq j, m_k = m_j} \frac{\partial q_k}{\partial p_j} \frac{p_k - c_k}{q_j} \in [-1, 0]$ where the cross partial terms will be positive because the products are (imperfect) substitutes.

B.3 Standard Errors

The parameter restrictions and multiple stages in the estimation procedure make it difficult to compute asymptotic standard errors directly; so I use a delete-one jackknife, constructing 96 sub-samples, each with one hospital deleted from the original data set. I sample hospitals instead of individual observations to allow for arbitrary correlation among the unobservables within a hospital (analogous to clustering standard errors at the hospital level). For each sample, I compute the demand estimates, supply estimates, and counterfactuals; and I then use the standard deviation in these estimates across the samples as the standard errors.

C Robustness

This Appendix conducts several specification and robustness checks, focusing especially on the demand estimates, which are critical for the analysis in this paper. C.1.1 estimates a series of specifications using a simple logit demand system in order to verify that the basic identification approach works. C.1.2 demonstrates the importance of allowing for more flexibility in the demand curve with the nested logit random coefficients and the mixture terms which allow for brand loyalty. C.1.3 checks the robustness of the demand estimates to estimating from a subsample of the data and including time dummy variables. C.2 checks robustness of the paper's results to various assumptions on stent marginal costs.

C.1 Demand Estimation Specification and Robustness

C.1.1 Identifying the Effect of Price on Demand

Table 11 illustrates how the stent-hospital fixed effects, AR(1) error process, and instrumental variables identify the price sensitivity coefficient in the context of a simple logit model of demand: $\ln(s_{jht}/s_{0ht}) = \theta^p p_{jht} + X_{jht}\theta^x + \xi_{jht}$. Though the logit restricts the shape of the demand curve and thus does a poor job of estimating own and cross-elasticities, it will consistently estimate the average price effect, and it provides a simple context that focuses on this effect in order to see the identification strategy at work.

Table 11: Identifying the Effect of Price on Demand: Logit demand estimates from: $\ln(s_{jht}/s_{0ht}) = \theta^p p_{jht} + X_{jht}\theta^x + \xi_{jht}$ for different specifications to illustrate how the fixed effects, AR(1) term, and instrumental variables identify the effect of price on demand.

parameter	OLS	stent-hospital FE	FE & AR(1)	IV
ρ (persistence in demand unobservable)	-	-	0.26	0.26
			(0.004)	(0.004)
θ^p (price sensitivity in $\frac{utils}{\$1000}$)	0.98	-0.63	-0.67	-0.73
	(0.04)	(0.02)	(0.02)	(0.03)

N=10,098. All s.e. clustered by hospital ($N_{Hospitals} = 96$).
First stage F-test for IV strength: $F = 664$.

OLS results in a positive price coefficient, consistent with the standard problem of unobserved demand heterogeneity that is correlated with price. Both the institutional accounts of demand heterogeneity and the economics of identifying demand with negotiated prices suggest adding stent-hospital fixed effects and relying on within stent-hospital variation over time. The resulting negative price coefficient suggests that this approach is well-founded. Institutional knowledge also suggests that even within a stent-hospital, demand may evolve over time with some amount of persistence, and the result of adding an AR(1) component in addition to the fixed effects suggests that this is indeed the case.

If prices are always set at the beginning of the month (and do not incorporate future changes to demand that are not incorporated into current demand), then there may be no further endogeneity/simultaneity problem. To avoid this potentially strong assumption, the paper's analysis of the economics of negotiated prices suggests that both lagged own price and mean lagged other prices would be valid instrumental variables. Using these instruments increases the magnitude of the price coefficient by approximately 9%. The results of the first-stage regression of price on these instruments and the other regressors shown below in Table 12 indicate that both are strongly correlated with price; and under the timing assumption discussed in the paper—that price does not incorporate known changes in future demand that are not already captured in current demand—the instruments are also uncorrelated with the unobservable innovation in demand ($\widetilde{\xi}_{jht}$).

Table 12: First-stage IV Regression: Price (p_{jht}) regressed on instrumental variables of lagged own price (p_{jht-1}) and lagged average price of other stents at the same hospital ($\sum_{k\neq j} p_{kht-1}/K_{ht-1}$) and the other regressors.

p_{jht-1}	$\sum_{k\neq j} p_{kht-1}/K_{ht-1}$	F(2,95) statistic
0.68	0.033	664
(0.02)	(0.016)	

N=10,098. All s.e. clustered by hospital ($N_{Hospitals} = 96$).

C.1.2 Allowing for Nonlinearities in the Demand Curve

Whereas the stent-hospital fixed effects and AR(1) term capture heterogeneity in demand across hospitals and time, institutional knowledge suggests that there is significant heterogeneity across patients and doctors within a hospital. While the logit can identify average price effects, it does so by fitting a demand curve that has relatively little curvature and thus restricts substitution patterns between products. Providing a demand specification that is flexible enough to "allow the data to speak" is especially important for a study such as this one where so much hinges on the nature of demand. Table 13 shows estimates for the logit, for a nested logit with random coefficients on the stent versus no stent and DES versus BMS, and for a mixture of nested logits that allows each stent to have its own mean-shifter for some set of patients/doctors.

The results show that allowing for a more flexible demand curve is important for explaining the data. The random coefficient on stents versus the outside good captures the fact that some patients need a stent while others don't. The random coefficient on DES captures the fact that some patients (or their blockage type) may not be appropriate for a DES or the fact that some doctors may favor DES more than others at a given hospital. The random mean shifters capture the fact that some stents can be especially appropriate for a specific type of patient and the (now confirmed) institutional belief that doctors can be intensely loyal to their preferred stent(s).

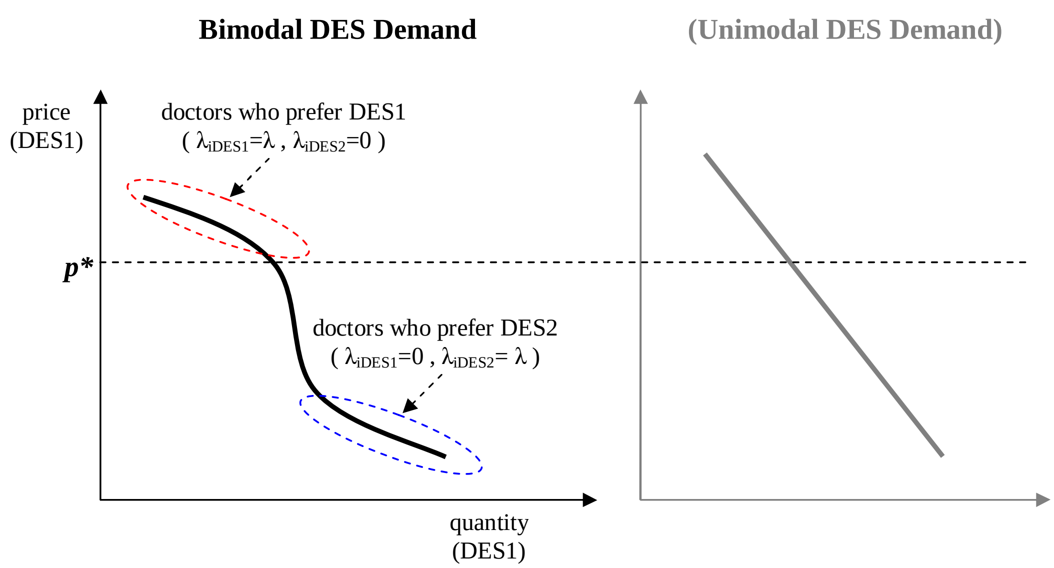
These nonlinearities in demand are especially important in their implications for pricing. The "brand-loyalty" evident here provides an incentive to keep prices high to extract surplus from loyal customers, as shown in Figure 7.

Table 13: Demand Specifications: Nonlinear Demand Parameters

parameter	Logit	Nested Logit	Mixture of NL (Paper)
ρ (persistence in demand unobservable)	0.26	0.10	0.08
	(0.004)	(0.002)	(0.002)
θ^p (price sensitivity in $\frac{utils}{\$1000}$)	-0.73	-0.29	-0.27
	(0.03)	(0.02)	(0.02)
σ_{stent} ("correlation" in demand for stents)	-	0.56	0.38
		(0.04)	(0.05)
σ_{des} ("correlation" in demand for DES)	-	0.31	0.29
		(0.02)	(0.02)
λ_{des} (shift for loyal user of each DES)	-	-	3.3
			(0.3)
λ_{bms} (shift for loyal user of each BMS)	-	-	2.0
			(0.2)
mean BMS own-elasticity	-0.61	-0.56	-0.32
mean DES own-elasticity	-1.38	-2.05	-0.52
mean outside option cross-elasticity	0.08	0.04	0.03
GMM criterion	161.2	16.25	15.19

N=10,098. All s.e. clustered by hospital ($N_{Hospitals} = 96$).

Figure 7: Bimodal versus unimodal demand for DES. The random mean, λ_{ijht}, allows the distribution of doctor/patient tastes to be *bimodal*. A bimodal distribution implies a demand curve with multiple groups of consumers, each with similar willingness-to-pay, whereas a unimodal distribution does not; and these two situations have very different implications for pricing—in particular near a price such as p^* in the figure.



C.1.3 Robustness to Sample Time and Control Variables

The demand model used in the paper represents my preferred specification, balancing parsimony with flexibility in capturing the heterogeneity across hospitals and patients.

Table 14 shows the results of robustness checks that (1) estimate the same model on the subset of the data before the DES safety scare, and (2) estimate the same model with month fixed effects added.

Table 14: Demand Robustness

parameter	Paper	2004-06	Month FE
ρ (persistence in demand unobservable)	0.08	0.09	0.08
	(0.002)	(0.006)	(0.003)
θ^p (price sensitivity in $\frac{utils}{\$1000}$)	-0.27	-0.31	-0.15
	(0.02)	(0.03)	(0.03)
σ_{stent} ("correlation" in demand for stents)	0.38	0.26	0.46
	(0.05)	(0.03)	(0.14)
σ_{des} ("correlation" in demand for DES)	0.29	0.23	0.41
	(0.02)	(0.02)	(0.09)
λ_{des} (shift for loyal user of each DES)	3.3	3.95	3.25
	(0.3)	(0.3)	(1.0)
λ_{bms} (shift for loyal user of each BMS)	2.0	0.0	2.0
	(0.2)	(0.1)	(0.8)
mean BMS own-elasticity	-0.32	-0.41	-0.17
mean DES own-elasticity	-0.52	-0.62	-0.28
mean outside option cross-elasticity	0.03	0.07	0.03

N=10,098. All s.e. clustered by hospital ($N_{Hospitals} = 96$).

The results across the robustness checks are all qualitatively similar. In particular, demand is relatively inelastic, consistent with the institutional facts about doctor price-sensitivity and negotiated prices. Quantitatively, the results of the two robustness checks are close to those of the main specification from the paper, though they differ in some ways that make sense.

The results from running the model on the period before the DES safety scare (Jan. 2004 - Feb. 2006) show slightly more elastic demand estimates, and in particular less brand loyalty among BMS. This makes sense because the DES safety scare provided exactly the type of variation that was useful in pinning down how inelastic demand really was, especially the substitution patterns to and between BMS.

The results from adding month fixed effects to the model show elasticities almost half of those in the main specification, driven entirely by a decrease in the price sensitivity parameter, θ^p. This move is in the opposite direction of what would be expected if there were residual correlation between the demand unobservable and price variable in the main specification (month fixed effects will soak up any month-specific unobserved variation in the value of stenting versus alternative options that affects all stents and all hospitals). A perhaps more plausible explanation for the decrease in the price coefficient with month fixed effects is attenuation bias—because of the stent-hospital fixed effects and AR(1) process, identification comes from within stent-hospital variation over time, and including month fixed effects absorbs some of this variation, biasing the price coefficient towards zero. The fact that standard errors increase dramatically in this specification is also consistent with attenuation from the time fixed effects absorbing useful variation over time in the data.

C.2 Robustness to Cost Estimates

Cost parameters are not tightly identified in this application because the large amount of product differentiation leads to added values that are always much larger than marginal costs. The flip side of this situation is that even large changes to the cost numbers induce relatively small changes in bargaining ability and counterfactual estimates. Table 15 shows the results of these estimates for costs fixed at zero, the estimated costs in the paper ($c_{bms} = 34, c_{des} = 1103$), and costs fixed at the minimum observed prices in the data ($c_{bms} = 240, c_{des} = 1540$).

Table 15: Robustness to Various Cost Assumptions

	$c_{bms} = 0, c_{des} = 0$	Paper $c_{bms} = 34, c_{des} = 1103$	$c_{bms} = 240, c_{des} = 1540$
mean bargaining split, $\frac{b_j(h)}{b_j(h)+b_h(j)}$, (0, 1)	0.43	0.33	0.25
std. dev. bargaining split, $\frac{b_j(h)}{b_j(h)+b_h(j)}$, (0, 1)	0.15	0.07	0.07
mfr profits, ($M/hospital/year)	2.18	1.24	0.84
hospital surplus, ($M/hospital/year)	4.32	4.32	4.32
mean DES price, ($/unit)	2509	2509	2509
mfr profit change for $b_{\mathcal{H}} = \beta_h$, (%)	5.5	8.0	10.7
hospital surplus change for $b_{\mathcal{H}} = \bar{\beta}_h$, (%)	-3.1	-1.4	-1.2
mean DES price change for $b_{\mathcal{H}} = \bar{\beta}_h$, (%)	5.2	1.7	0.7

The results of varying the cost parameters show that, as expected, bargaining ability estimates change, but less dramatically than the cost changes. The level of manufacturer profits are directly related to costs and thus sensitive to price changes, but manufacturer profit *changes* under the counterfactuals are less sensitive to the cost changes. The different manufacturer bargaining abilities implied by the different costs does lead to different price increases under the more uniform pricing counterfactual, which leads to different hospital surplus changes. Overall, these robustness checks confirm that, even under these two extreme cost possibilities, the results are quantitatively similar and qualitatively identical.