Price Discrimination and Product Variety: The Case Of Implantable Medical Devices

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Abstract

Implantable medical device manufacturers are able to directly price discriminate by setting different prices for the same product in different hospitals. I analyze the welfare effects of this form of price discrimination in the case of Implantable Cardioverter Defibrillators (ICDs). I find that if ICD manufacturers switch to uniform pricing, prices increase on average, which causes a decline in hospital welfare and manufacturer profits. Allowing manufacturers to indirectly price discriminate by strategically delaying the exit of old products to target their elastic consumers causes an increase in product variety. As a result, net hospital surplus increases by 3.4% relative to price discrimination, but the consumption of new, higher quality ICDs drops by 19.3%. Relative to price discrimination, manufacturer profits under uniform pricing decline by 6.6%-12.5%.

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1 Introduction

Implantable medical device manufacturers practice direct (third-degree) price discrimination by setting different prices for the same product in different hospitals. As a result, prices of the same device can vary between hospitals by thousands of dollars (GAO, 2012). There has been substantial discussion in the policy literature about making prices more uniform in this industry (for example, see Lind (2017)).[2] However, economic theory predicts that the effects of direct price discrimination on prices and welfare are ambiguous (Holmes, 1989).

Furthermore, if direct price discrimination were prohibited, multiproduct manufacturers might change their product offerings and use products that are vertically differentiated for indirect price discrimination. Specifically, manufacturers may introduce lower quality products, or keep existing low-quality products on their shelves for a longer period. These low-quality products can be targeted toward elastic consumers, while higher quality products are targeted toward inelastic consumers. In this paper, I use the context of Implantable Cardioverter Defibrillators (ICDs), in which manufacturers are counterfactually not allowed to directly price discriminate, and I ask two questions: First, would ICD manufacturers delay the exit of their older products and use these products to price discriminate indirectly? Second, if so, how would this affect hospital (consumer) welfare, manufacturer profits, total surplus, and the adoption of newer, higher quality products?

ICDs are devices that reduce the risk of sudden cardiac death in at-risk patients. They are implanted in a patient's chest and deliver a shock to their heart when an abnormal heart rate is detected. A recent innovation in ICDs led to the rapid exit of old products

research. The data in this paper is from GlobalData Plc. I am grateful to Dr. Matthew Reynolds, Dr. Douglas Mah, and David Walsh, for sharing with me their insights about the industry. GlobalData did not play a role in this paper beyond giving me the data. Any errors are mine.

[2] Following is an excerpt from my conversation with the supply chain director of a major hospital in Boston: *"It would be great if they (manufacturers) were charging $2000 for the same pacemaker across all hospitals instead of $1800 in one and $5000 in another."*

and entry of new products. Prior to 2015, Magnetic Resonance Imaging (MRI) scans were costly to perform in patients (Nazarian et al., 2011). In September 2015, the first MRI-safe ICD was approved by the Food and Drug Administration (FDA) in the US.[3] MRI-safe ICDs make it easier for patients to undergo MRI scans, but are more expensive than the older ICDs without this feature (MRI-unsafe ICDs). By late 2017, all manufacturers had received their FDA approvals for MRI-safe ICDs, and almost all MRI-unsafe ICDs were phased out by the end of 2018.

I use a detailed dataset on the prices and quantities of ICDs purchased by a sample of hospitals in the US in 2014-2019 to estimate a model of supply and demand for ICDs. On the supply side, in the beginning of each year, I assume that manufacturers observe the fixed cost of offering each product in that year, and simultaneously determine their product offerings. After choosing their product offerings, manufacturers observe demand and marginal cost shocks and simultaneously set prices. On the demand side, a physician-patient pair makes a discrete choice for an ICD, conditional on product offerings. I use the model to estimate demand parameters and marginal costs, and to bound the fixed costs of offering each product in a year. Then, I do the following counterfactual analysis: in each time period, I require ICD manufacturers to set the same price for each product across all hospitals. I assume that in addition to the products manufacturers actually offer in the observed equilibrium with direct price discrimination, manufacturers have the option of continuing to offer their MRI-unsafe ICDs that were (in reality) phased out after FDA approval was granted for the new MRI-safe products. Given the demand parameters, marginal cost parameters, and fixed cost bounds, I find the set of possible equilibria that exist under this uniform pricing policy. Under each equilibrium, I calculate the change in hospital surplus, manufacturers' profits, and total surplus relative to the observed equilib-

[3]The technical term for an MRI-safe ICD is "MR-conditional ICD". This is because these ICDs are safe to perform MRI scans with, under certain conditions. In the rest of this article, I will use MRI-safe ICD to refer to an ICD with the MR-conditional feature, and MRI-unsafe ICD to refer to an ICD without the MR-conditional feature.

rium with direct price discrimination.

Holding manufacturers' product offerings fixed, I find that under a uniform pricing policy, manufacturers would price products to serve their inelastic consumers, resulting in higher prices and lower expected hospital surplus by 5.2%.[4] The higher prices under uniform pricing would reduce the demand for ICDs by more elastic consumers, and expected profits for the two largest manufacturers in my data would drop by 9% and 3.1% respectively. Expected total surplus would drop by 6.1%.

Under a counterfactual that allows product offerings to be endogenously determined, I find starkly different results under a uniform pricing policy. Each of the two largest manufacturers in my data continue to offer an MRI-unsafe product in my *preferred* equilibrium.[5] As a result, product variety increases, and prices fall due to stronger manufacturer competition between the additional rival products. This causes expected hospital surplus to increase by 3.4% relative to price discrimination. However, elastic consumers substitute to the lower quality option, and the purchase of ICDs that are equipped with the newer MRI-safe technology drops by 19.3%. On the manufacturers' side, a competitive equilibrium that causes each manufacturer to continue offering an MRI-unsafe product, reduces profits, relative to a case in which no manufacturer continued to offer an MRI-unsafe product. The business-stealing effects of their rival's additional product, the inability of manufacturers to recover all the consumers that were lost due to the higher prices under uniform pricing, and the fixed costs of offering this additional product, cause total profits of the two largest manufacturers in my data to drop by 9.4-12.5% and 6.6-8.8% respectively, relative to the price discrimination case. In this equilibrium, the drop in expected total surplus relative

[4]Patient surplus in this setting depends on the pass-through of ICD prices to patients through insurance premiums, which is outside the scope of this paper. Surplus measures in this paper should be interpreted as hospital surplus, keeping insurance premiums fixed.

[5]Three equilibria exist for the range of estimated fixed costs. In each of these equilibria, either one or two older, cheaper, MRI-unsafe ICDs would continue to be offered. Of these equilibria, my *preferred* equilibrium exists for the widest range of fixed costs in my estimated intervals.

These two manufacturers account for about 90% of the ICD sales in my data.

to the price discrimination case ranges from 1.5-2.6%. Thus, failing to account for manufacturers' ability to change their product offerings in response to a uniform pricing policy reverses the estimated effects of price discrimination on hospital welfare, underestimates its effects on manufacturer profitability, and overestimates its effects on the purchase of high quality products.

With this paper, I contribute to the vast literature on the effects of price discrimination, and to the growing literature that treats product line decisions by manufacturers as endogenous. To my knowledge, this is the first paper that combines these two strands of literature to answer the question of whether manufacturers would keep older products on the market to indirectly price discriminate if they are unable to do so directly. Theory predicts that the consumer welfare effects of uniform pricing relative to third-degree price discrimination are ambiguous. When product offerings are held fixed, they depend on the heterogeneity in brand loyalties between markets (Holmes (1989) and Borenstein (1985)). (Mussa and Rosen, 1978) predicts a downward distortion of quality by firms that offer quality differentiated products. Varian (1985) finds that price discrimination can increase total welfare only if it increases aggregate output.

The empirical paper that is closest to mine in context is Grennan (2013), who analyzes the welfare effects of price discrimination in the industry for a different type of implantable medical device: cardiac stents. Grennan (2013) assumes that product offerings are fixed and finds results that are qualitatively similar to mine when I hold product offerings fixed; under a uniform pricing policy, if hospitals were price-takers (the Nash Bertrand assumption) heterogeneity in brand loyalties across hospitals would lower competition and lead firms to price higher than the average. This would lead to hospital welfare losses, and Grennan (2013) finds that hospitals would need large increases in their bargaining abilities for uniform pricing to improve their welfare.[6] I endogenize product offerings of manufac-

[6] Grennan (2013) models the price-setting process as a Nash-in-Nash bargaining model. See footnote 18 for details about why I assume a Nash Bertrand equilibrium.

turers in each period, and show that even if hospitals are price takers (i.e. even if hospitals have no bargaining ability), the increased product variety under uniform pricing can cause an increase in hospital welfare relative to price discrimination.

Price discrimination using products that are vertically differentiated in quality is a form of second-degree price discrimination. Most empirical papers on price discrimination analyze the effects of either second or third degree price discrimination separately. Some exceptions to this are Leslie (2004), which quantifies the welfare effects of second and third degree price discrimination in ticket sales for a Broadway show. Aryal et al. (2021) uses airline data to model second degree price discrimination (economy versus first class) and third degree price discrimination (based on passengers' reasons to travel). Chandra et al. (2020) also uses the airline setting to show how the two types of price discrimination interact. Mortimer (2007) finds that in the absence of the ability to directly price discriminate, indirect price discrimination in movie distribution increases consumer welfare. I contribute to this literature by explicitly modeling both types of price discrimination, and then in a counterfactual shutting one type (third degree price discrimination) off, and studying its effects on the other type (second degree price discrimination).

Some recent examples of papers that treat product offerings as endogenous are Draganska et al. (2009), Fan (2013), Nosko (2010), Wollmann (2018), Eizenberg (2014), Ciliberto et al. (2018), and Fan and Yang (2020a). Many of these papers focus on the effect of competition on product variety. For example, Draganska et al. (2009) simulate an ice-cream merger and estimate its effects on product variety and prices. Eizenberg (2014) quantifies the effect of a new technology introduction in an upstream market (CPUs) on product offerings in the downstream market (CPU-PC configurations). It uses the idea that the observed equilibrium is an Subgame Perfect Nash Equilibrium from which there is no single profitable deviation, to partially identify fixed costs. There is a selection issue that arises when fixed costs are estimated this way; products that are offered in a particular period may have had low fixed cost draws, and those that are not offered may have had high draws. I account for selection in estimated fixed costs using the method in Eizenberg (2014). Other methods to deal with selection have also been used in recent literature. For example, Pakes et al. (2015) demonstrates several examples of instruments that are exogenous to fixed costs and can be used to get unbiased estimates of fixed costs. Wollmann (2018) isolates periods with exogenous demand shocks (that are uncorrelated with fixed costs), in which product entry or exit is certain to occur, and uses these periods to estimate fixed costs.

The rest of this paper is organized as follows: Section 2 describes the industry for ICDs, the new MRI-safe technology that was introduced in the US, and my data sources. Section 3 presents three motivating facts which should convince the reader that ICDs are an appropriate context for my research question. Section 4 describes the empirical model of supply and demand, and section 5 describes how I estimate the model. My estimation results are in section 6. The counterfactual description and results are in section 7. I conclude in section 8.

2 Institutional setting and Data

2.1 Implantable Cardioverter Defibrillators

Sudden cardiac death accounts for about 7-18% of all deaths in the U.S (Stecker et al., 2014). Implantable Cardioverter Defibrillators (ICDs) are implantable medical devices that prevent sudden cardiac death in patients that experience life threatening arrhythmias.[7] An ICD is implanted in a patient's chest, and connected to their heart via leads (see figure 5 in appendix A.4). It reduces the risk of death due to sudden cardiac arrest by shocking an implanted patient's heart when it detects a dangerously abnormal heart rate.

[7]https://www.heart.org/en/health-topics/arrhythmia/prevention–treatment-of-arrhythmia/implantable-cardioverter-defibrillator-icd

The industry for implantable medical devices in general is oligopolistic; in the case of ICDs, 4 manufacturers capture more than 95% of the market share. A feature of the industry for implantable devices such as ICDs is that the prices that hospitals pay for these devices are confidential, and device manufacturers are able to third-degree price discriminate, i.e. they are able to charge different hospitals different prices for the same product. Medicare usually reimburses hospitals for the cost of the entire medical procedure, not separately for the individual cost of an implantable device. Therefore, hospitals benefit from buying these devices at lower prices (see Lind (2017)).[8] The causes and effects of the lack of price transparency in this industry have often been a subject of discussion in the medical literature.[9]

Each manufacturer in this industry produces multiple brands of ICDs, and within each brand offers multiple differentiated products. ICD manufacturers are extremely innovative, and are always trying to compete to produce the most cutting-edge devices. After a manufacturer invents a new type of device, it applies for regulatory approval in different countries. In the US, a manufacturer is able to market its new devices after it gains approval from the Food and Drug Administration (FDA).

2.2 The innovation

Magnetic Resonance Imaging (MRI) scans are contraindicated in patients with traditional ICDs. This is because the magnetic fields formed by MRI machines can react with the device and cause damage to the device, leads, or heart (Do and Boyle, 2016). Some studies estimate that 50-75% of patients with ICDs will need an MRI scan during the lifetime of the device (Kalin and Stanton, 2005). Thus, an important innovation in the 2010s was development of MRI-safe ICDs, which are ICDs that are safe to perform an MRI scan with,

[8]In some cases, when Medicare does reimburse hospitals for actual device prices, they do not know the actual price that the hospital paid for the device, so they pay a fixed rate across all hospitals.

[9]For example, see Pauly and Burns (2008) and the MedPac Report to the Congress (2017) on Medicare

under certain conditions. In fact, the following is a quote from Sethi et al. (2018):

"*It is difficult for the physician to justify the implantation of a conventional system if an MRI-compatible system is available.*"

The first manufacturer to receive FDA approval for an MRI-safe ICD in the US was Medtronic, in September 2015. Soon after this, other manufacturers started receiving their first FDA approvals for the same technology. After these manufacturers received their first FDA approval for an MRI-safe ICD, they started phasing out their older, MRI-unsafe ICDs and introducing newer, MRI-safe ones, often under the same brand name as the older versions. The last manufacturer to receive its approval was St Jude Medical in September 2017. By late 2018, almost all MRI-unsafe ICDs had been phased out.[10]

The FDA generally has longer approval times than Europe. When this technology was first introduced in the US, all the manufacturers had already received approval in Europe for their MRI-safe ICDs (see Figure 7 in Appendix A.4). The timing of a new device introduction depends on the lengthy FDA approval process, and it was the approval of this technology in the US that led to the phasing out of older, MRI-unsafe devices.

2.3 Data

GlobalData Plc is a market research company that has detailed data on prices and purchase volumes of medical devices. I have obtained monthly data on self-reported prices paid and quantities purchased of ICDs at the SKU level, by 868 healthcare facilities in the US from 2014-2019 from GlobalData.[11] The healthcare facilities in this database are anonymous, and the only information I have about them are 1) their census region (Midwest, Northeast,

and the Healthcare Delivery System

[10] In 2019, 98% of ICD sales in my final sample were for MRI-safe ICDs

[11] One of the manufacturers, Boston Scientific, had several confidentiality clauses built into their contracts with the healthcare facilities. There is significant under-reporting in purchases from Boston Scientific, because of which I drop purchases from this manufacturer from my analysis, and account for it while defining market sizes. Details are in appendix A.2. Microport Scientific is another manufacturer that sells ICDs. However, it accounts for less than 1% of transactions in my data, so I drop it from my analysis.

South, and West) and 2) their bed size. Together, the purchases from these facilities account for about 30% of total ICD sales in the US.

For each product, I have obtained some information on product characteristics from GlobalData, and have compiled the other information by looking through product manuals from manufacturer websites. There are broadly two types of ICDs, single chamber and dual chamber ICDs, which differ from each other based on the number of leads that are used to connect them to the heart.[12] I obtained data on the MRI-safe status of each SKU from the product manuals found in manufacturer websites. From these product manuals, I also collected information about whether or not an ICD had a DF-4 lead connector, which is a technology that made devices less bulky and easier to implant with a lower risk of complications.

The last two pieces of data I collect are: 1) FDA approval dates for the MRI-safe products of each brand. I collect this data from the FDA's publicly available Pre-Market Approval (PMA) Database (FDA, 2021) and 2) Annual Medicare prescriptions of the most popular anti-arrythmiatic drug from 2014-2018, which I collect from the the Part D Prescriber Public Use Files (CMS, 2018). I use this prescription data to construct a measure of the outside option for demand estimation (see Appendix A.2 for details).

My data cleaning process has been described in Appendix A.2. After cleaning my data, my final sample contains 25,878 observations: it is an unbalanced panel of prices and purchases of ICDs at the SKU level, by 727 hospitals from 3 manufacturers in the 12 six-month periods from 2014-2019.

[12]There is third type of ICD known as a CRT-D, which uses 3 leads, but I exclude these from my analysis, because 1) In addition to the ICD function, they provide an additional function which is to re-synchronize the ventricles of the heart, and hence are less substitutable with single/dual chamber ICDs 2) They cost hospitals about 31% more than dual and 47% more than single chamber ICDs respectively 3)They are usually sold under a different brand names than the single/dual chamber ICDs. My results are

3 Motivating facts

The industry for ICDs in 2014-2019 is an appropriate setting in which to analyze whether banning direct price discrimination would cause manufacturers to continue offering older products for the purposes of indirect price discrimination. This is because of two facts: 1) price discrimination in this industry and 2) the FDA approval of the MRI-safe technology during this period led to the exit of older, MRI-unsafe ICDs.

3.1 Price discrimination

Implantable Medical Device manufacturers set different prices for the same product (SKU) in different hospitals. Examples of this can be seen in figure 1, which documents the variation in price paid for the same Implantable Cardioverter Defibrillator (ICD) between hospitals in each quarter for the most popular product (in terms of sales) of the largest firms in my data (see Figure 6 in Appendix A.4 for more examples). The difference between the 25th and 75th percentile of these prices is always a few thousand dollars, and the difference between the maximum and minimum prices paid for the same product can be as high as $10,000. One might believe that this observed variation in prices could have explanations other than market segmentation. For example, this variation could be driven by quantity discounts or exclusive contracts, rather than third degree price discrimination. I conduct several exercises which suggest that while quantity discounts and exclusive contracts do seem to exist in this industry, they account for a small fraction of the total variation in prices paid between hospitals. The results of these exercises are in appendix A.3.

3.2 MRI-safe ICDs

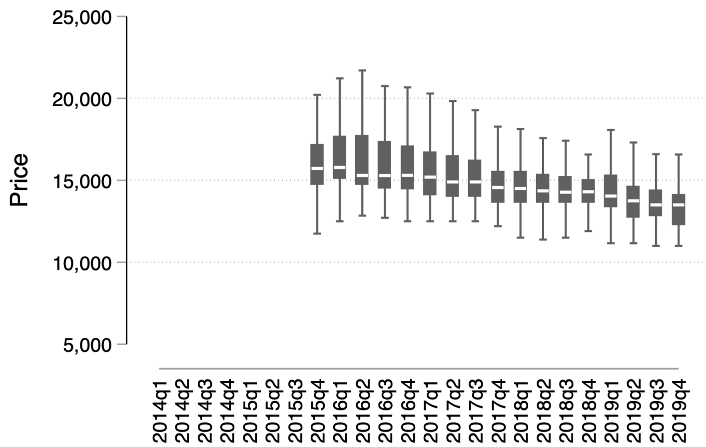
The first MRI-safe ICD received FDA approval in late-2015, after which manufacturers started phasing out their older, MRI-unsafe ICDs. The top panel of figure 2 shows that by 2019, only 2 out of 19 products offered by the three manufacturers in my dataset were MRI-unsafe. The bottom panel of figure 2 shows that MRI-safe ICDs account for almost all ICD sales in my sample by 2019.

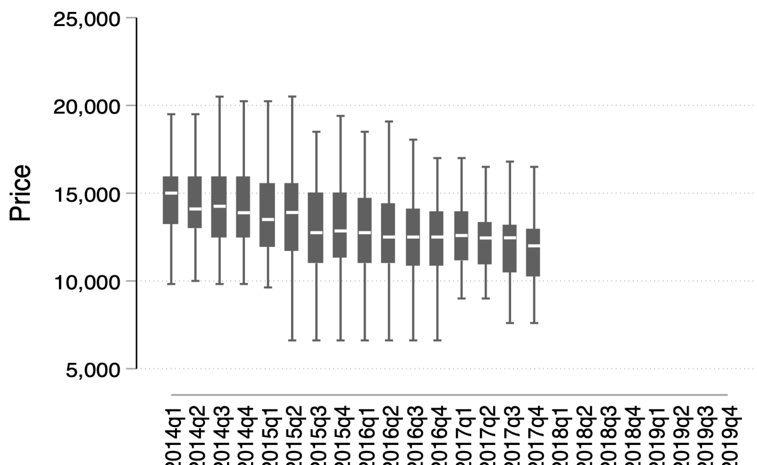
Table 1 reports the entry-exit pattern of products (SKUs) belonging to the most popular brand of the two largest manufacturers in my data. These brands account for 79% and 60% of total sales volumes of Medtronic and St Jude Medical respectively over the period of my data. From table 1, it can be seen that none of the products from these brands were offered for the entire duration of my data. Medtronic received approval for its first MRI-safe ICDs in late 2015, after which it phased out some of its MRI-unsafe products. However, it continued to offer some MRI-unsafe products until late 2017, which is when its rival, St Jude Medical, received its first MRI-safe ICD approval.

Table 1 shows that Medtronic also phased out some of its MRI-safe ICDs in 2017. This could be driven by the fact that it introduced a new brand in 2016 with MRI-safe ICDs of the same device type. The exit of these products may not directly be driven by the introduction of MRI-safe ICDs, so I keep these products fixed in the counterfactual, i.e. I do not endogenize the entry-exit decision of these products in the counterfactual.

robust to including CRT-Ds. Boston Scientific invented leadless/subcutaneous ICDs in 2012, but I exclude these from the analysis due to the reasons in footnote 11.

Figure 1: Motivating fact 1: Price variation





This figure has box plots of prices of the most popular product (in terms of total sales over 2014-2019) of Medtronic (top) and St Jude Medical (bottom), which are the top 2 manufacturers in my data, over time. Each box documents the variation in prices of the same product in a particular quarter between hospitals. The upper hinge of each box is the 75th percentile of prices, the lower hinge is the 25th percentile.

Table 1: Motivating fact 2: MRI-safe technology

Firm	MRI-safe	Product	2014	2015	2016	2017	2018	2019
Medtronic Plc	No	A	O	O				
	No	B	O	O	O			
	No	C	O	O	O			
	No	D	O	O	O	O	O	
	No	E	O	O	O	O		
	No	F	O	O	O			
	Yes	G			O	O		
	Yes	H			O	O		
	Yes	I			O	O	O	O
	Yes	J				O	O	O
St Jude Medical	No	A	O	O	O	O		
	No	B	O	O	O	O	O	
	No	C	O	O	O	O	O	
	No	D	O	O	O	O		
	Yes	E					O	O
	Yes	F					O	O

This table shows the products of the top-selling brand of the two largest firms in my data.
O in this table denotes that the product was offered in that year, and a blank space denotes that it was not offered
MRI-safe ICDs are in the gray portion of the table, and MRI-unsafe ICDs are in the white portion
I have removed a small number of products that were offered in only one year from this table.

4 Empirical Model

4.1 Overview

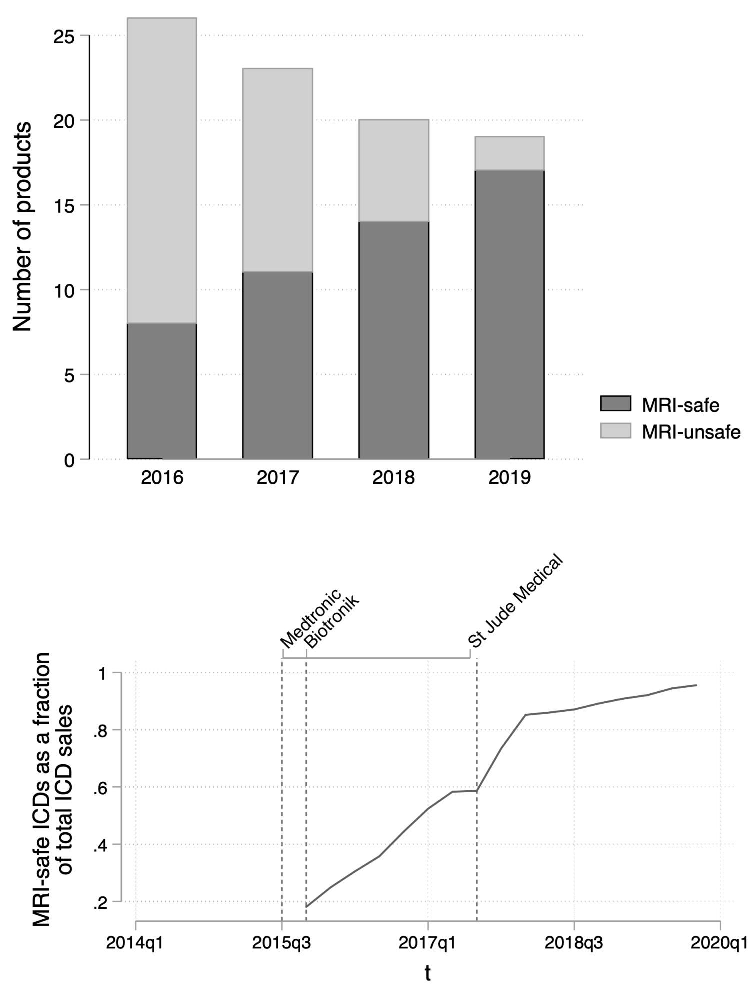
In this section, I set up my empirical model of supply and demand. The supply-side decisions of manufacturers take place in two stages:

- **Stage 1:** In the beginning of each year, manufacturers observe the fixed costs of offering each product and simultaneously choose their product offerings.

- **Stage 2:** After choosing their product offerings, in each six month period manufacturers observe demand and marginal cost shocks, and simultaneously set prices in a Nash Bertrand game.

I assume that the product entry-exit decision of a manufacturer is at the annual level, but demand and price setting are modeled at the six month level. The assumption

Figure 2: Motivating fact 2: MRI-safe ICDs



The top panel of this figure plots the number of products that were MRI-safe and MRI-unsafe in each year from 2016-2019. The bottom panel of this figure plots MRI-safe ICD purchase volumes as a fraction of total ICD purchase volumes by all hospitals and manufacturers in my sample. The vertical lines show you when each manufacturer in my data received approval for their first MRI-safe ICD. I exclude Boston Scientific from this picture due to the reasons in footnote 11.

that manufacturers observe demand and marginal cost shocks after choosing their product offerings is crucial for identifying demand and correctly measuring the variable profits of a manufacturer. Without this assumption, these shocks would determine product entry and exit, and hence the observed choice sets of consumers, which would create a sample selection issue.

On the demand side, a physician in a health care facility sees a patient, and conditional on product offerings makes a discrete choice for an ICD (or the outside option).

This model is solved backwards. In the following subsections I will describe my model in more detail.

4.2 Demand

A market is a hospital in a six month period, and a product is an SKU.[13] I aggregate my data to the six-month level because 1) ICD purchases in each month are low, and aggregating up helps me reduce the number of zeros in my data 2) Prices are very sticky at the product-hospital level over time (see table 8 in appendix A.3).[14]

A patient visits an electrophysiologist (a physician that does ICD implants) in hospital h during the six month period t. I denote this physician-patient pair as i. The utility that i in hospital h gets from an ICD j belonging to brand b at time t is[15]

$$U_{ijht} = \beta_c^i + \beta_{bh} - \beta_p^i p_{jht} + \mathbf{X_j}\beta_\mathbf{x}^\mathbf{i} + \beta_{year} + \xi_{jht} + \epsilon_{ijht}$$

where β_c^i denotes the constant and captures an agent's preferences for the inside option, β_{bh} is a brand-hospital fixed effect which captures average hospital level preferences for a

[13] A small number of St Jude Medical's products have the same SKU name in my data before and after they received approval for MRI-safe use. I treat these SKUs before they received MRI-safe approval as separate products from the post-approval ICDs.

[14] Conversations with analysts at GlobalData, physicians that implant ICDs and the supply chain director of a hospital in Boston have revealed that pricing contracts for ICDs tend to be long term.

[15] I differentiate between a brand and a product because a single brand has multiple products.

particular brand, p_{jht} denotes prices of product j in hospital h at time t, and β_p^i captures an agent's disutility from price. $\mathbf{X_j}$ captures the following product characteristics: the MRI-safe status of an ICD j, its device type (single/dual chamber), and whether or not it has a DF-4 connector. In other words, $\mathbf{X_j} = (MRI_j,\ dualchamber_j,\ DF4_j)$, where $dualchamber_j$ is a dummy variable that takes a value 1 if the ICD is a dual chamber ICD, and 0 if it is single chamber. $\beta_{\mathbf{x}}^i$ captures an agent's preferences for $\mathbf{X_j}$. β_{year} is a year fixed effect which captures the changing average value of the inside option over time. ξ_{jht} captures product-hospital-time level demand shocks. For example, if physicians transfer in or out of hospital h at time t, average preferences for a product j in hospital h would change at t, which would be captured by ξ_{jht}. If a patient is a particularly good fit for a particular ICD j, this is captured by ϵ_{ijht}.

I make the following assumptions:

1. $\beta_c^i = \sigma_c \nu_c^i$, where $\upsilon_c^i \sim N(0,1)$. [16]

2. $\beta_p^i = e^{\beta_p + \sigma_p \nu_p^i}$, where $\nu_p^i \sim N(0,1)$

3. $\beta_{\mathbf{x}}^{\mathbf{i}} = \beta_{\mathbf{x}} + \sigma_{\mathbf{x}} \nu_{\mathbf{x}}^{\mathbf{i}}$, $\sigma_{dualchamber} = 0$, $\sigma_{DF4} = 0$, $\nu_{MRI}^i \sim N(0,1)$

4. ϵ_{ijht} are I.I.D and follow a Type 1 extreme value distribution.

5. The mean utility of the outside option is 0.

6. The random coefficients ν_c^i, ν_p^i, and ν_{MRI}^i are independent from each other and from ξ_{jht}.

Random coefficients on the constant, prices, and on certain product characteristics allow greater flexibility in the demand model. I assume that the random coefficient on prices follows a log-normal distribution to ensure that β_p^i is always positive. I set $\sigma_{dualchamber}$

[16] β_c^i is mean zero because the constant could not be distinguished from brand-hospital fixed effects.

and σ_{DF4} to zero, and only allow a random coefficient on the preferences for an MRI-safe device. Assumptions 4-6 are standard in the literature, and allow me to denote predicted market shares as follows:

$$s_{jht} = \int \frac{exp(\delta_{jht} - \beta_p^i p_{jht} + \sigma_c \nu_c^i + \sigma_{\mathbf{x}} \nu_{\mathbf{x}}^{\mathbf{i}} \mathbf{x_j})}{1 + \sum_{k \in J_{ht}} exp(\delta_{kht} - \beta_p^i p_{kht} + \sigma_c \nu_c^i + \sigma_{\mathbf{x}} \nu_{\mathbf{x}}^{\mathbf{i}} \mathbf{x_k})} dF(\nu_c^i, \nu_p^i, \nu_{\mathbf{x}}^{\mathbf{i}})$$

where $F(\nu_c^i, \nu_p^i, \nu_{\mathbf{x}}^{\mathbf{i}})$ is the joint distribution of the random coefficients, J_{ht} is the choice set of hospital h in time period t, and

$$\delta_{jht} = \beta_c + \beta_{bh} + \mathbf{X_j} \beta_{\mathbf{x}} + \beta_{year} + \xi_{jht}$$

Choice sets: Not all products are purchased by all hospitals in each time period. I assume that in each time period, a hospital's choice set consists of the products for which it has positive shares. This is a simplifying assumption, and it is reasonable in this setting because it is relatively uncommon in my data for hospitals to have temporary gaps in their purchases of a product.[17]

4.3 Supply

4.3.1 Stage 2

In stage 2, manufacturers observe the realizations of the demand and marginal cost shocks, and simultaneously set prices in a Nash Bertrand equilibrium.[18] The profit function of a manufacturer f in year y is as follows:

[17] Failing to account for products with zero shares can lead to biased demand estimates. In my setting, I aggregate my data to the six-month period to reduce the prevalence of zero shares. Some other solutions to this problem are to impute shares when there are zeros using methods in papers such as Gandhi et al. (2020) and Li (2017). In future versions of this paper, I plan to use these methods to expand the choice sets of agents and account for these zeros. If I expand the choice sets of my agents this way, 86% of the transactions in my data will continue be non-zero. Thus, this issue is unlikely to be a major concern in my setting.

[18] I depart here from the way Grennan (2013) models the price setting process for cardiac stents, a different implantable medical device. He uses a Nash-in-Nash Bargaining Model, rather than a Nash

$$\pi_{fy} = \underbrace{\sum_{t=1}^{2} \sum_{h \in H_{jt}} \sum_{j \in J_{fy}} (p_{jht} - c_{jht}) s_{jht}(\mathbf{p}) M_{ht}}_{\text{Variable profits } VP_{fy}} - \sum_{j \in J_{fy}} F_{jy} \tag{1}$$

t denotes the two six-month periods in a year y. J_{fy} is the set of product offerings of the manufacturer in year y (determined in stage 1), H_{jt} is the number of hospitals that purchase j at time t, and c_{jht} is the marginal cost of selling product j to hospital h at time t. M_{ht} is the market size. I construct an estimate of market size for each hospital-year using Medicare data on the annual number of unique beneficiaries for the most popular anti-arrhythmiatic drug, which is a common alternative to ICDs. Details on the construction of the market size can be found in appendix A.2. F_{jy} is the fixed cost of offering a product in each year. It is incurred if j is offered in year y.

I assume that the log of the marginal cost of selling a product depends upon its characteristics, an annual time trend, and a random shock. It has the following functional form:

$$log(c_{jht}) = \mathbf{Z_{jt}} \gamma_{\mathbf{z}} + \omega_{jht} \tag{2}$$

where Z_{jt} has a constant, ICD characteristics and year fixed effects. $\gamma_{\mathbf{z}}$ captures the effect of different product characteristics on the marginal cost of an ICD. ω_{jht} captures marginal cost shocks.

4.3.2 Stage 1

At the beginning of each year, manufacturers decide whether or not to keep a product in their set of offerings. They know the distributions of ξ_{jht} and ω_{jht}, but they do not observe

Bertrand assumption. The reason I depart from this assumption is that Grennan (2013)'s Nash-in-Nash Bargaining model assumes that the bargaining between hospital and device manufacturers takes place independently for each product. This is not realistic in my setting, where there are several brands offered the actual draws of ξ_{jht} and ω_{jht} prior to making their product portfolio decisions.

I broadly follow the revealed preference approach in Pakes et al. (2015) to obtain partially identified fixed costs. The idea is that the observed product offerings must be a Nash Equilibrium. Hence, no manufacturer has a profitable deviation from the observed product offerings, *given the choices of all other manufacturers*. These conditions generate moment inequalities which identify bounds on fixed costs.

Formally, suppose a product $j \in J_{fy}$, where J_{fy} is the set of observed product offerings by manufacturer f at year y. It must be that:[19]

$$E_{\xi,\omega}[VP_{fy}(J_{fy}, J_{-fy})] - F_{jy} \geq E_{\xi,\omega}[VP_{fy}(J_{fy} \backslash j, J_{-fy})] \tag{3}$$

where J_{-fy} denotes the observed product offerings of other manufacturers, $VP_{fy}(J_{fy}, J_{-fy})$ denotes variable profits of a manufacturer f in year y at the observed product offerings, and $VP(J_{fy} \backslash j, J_{-fy})$ denotes variable profits of a manufacturer if they drop j, keeping all other offerings (by f and competitors) fixed.

In words, if a product j is offered by manufacturer f in year y, it must be that the expected profits from offering it and paying its fixed cost are higher than the expected variable profits from not offering it, given all other product offerings. This expectation is over ξ and ω, whose values are not realized until the second stage.

Similarly, if product j is *not* offered by manufacturer f in year y, or if $j \notin J_{fy}$ it must be that

$$E_{\xi,\omega}[VP_{fy}(J_{fy}, J_{-fy})] \geq E_{\xi,\omega}[VP_{fy}(J_{fy} \cup j, J_{-fy})] - F_{jy} \tag{4}$$

by the same manufacturer, and each brand has multiple products. Moreover, it is crucial that I capture the multiproduct nature of manufacturers to answer my question about endogenous product offerings when price discrimination is prohibited.

[19] I model the entry decision at the annual level, which is why I use the y subscript in this section, unlike the demand and second stage of supply, which I model at the six month level (t). One can think of:

$$VP_{fy}(J_{fy}, J_{-fy}) = VP_{ft_1}(J_{fy}, J_{-fy}) + VP_{ft_2}(J_{fy}, J_{-fy})$$

Where t_1 and t_2 are the two six month time periods in year y.

i.e. if a product j is not offered by manufacturer f in year y, it must be that the expected variable profits from not offering j are higher than profits from offering j and paying the fixed cost.

Selection: In a year that product j is offered, equation 3 gives an upper bound on fixed costs, and in a year it is not offered, equation 4 gives a lower bound. The challenge is that I can either estimate an upper bound on the fixed cost of a product or its lower bound. Moreover, observed product offerings are not random, i.e. manufacturers are likely to offer products with low fixed cost draws in each year. This is the selection issue described in Pakes et al. (2015), and I follow Eizenberg (2014) closely to circumvent it. I assume that F_{jy}, which is the fixed cost of offering product j belonging to brand b in year y, takes the following functional form:

$$\frac{F_{jy}}{H_{jy}} = F^b + \eta_{jy}$$

where H_{jy} is the number of hospitals with j in their choice sets in year y, F^b is a brand specific component of fixed costs and $E(\eta_{jt}) = 0$, i.e the unconditional expectation of η_{jt} is zero. The assumption is that all fixed cost fluctuations over time and for products within a brand are random. However, we do not observe a random draw of η_{jy}. When a product is offered, it is likely to have had a low η_{jy} draw, and when it is not offered, it may have had a high η_{jy} draw. I make the following assumptions on the support of fixed costs, which are very similar to those that Eizenberg (2014) makes to resolve this issue:

1. F_{jy} is bounded from above and below.
2. F_{jy} belongs to the support of the expected changes in variable profit from adding or removing a single product of brand b, across all the products of brand b, and across all years.

Eizenberg (2014)'s justifications for these assumptions make sense in my setting. The assumption that fixed costs are bounded is reasonable, as I am estimating fixed costs for products that were offered at some point in my data, and not for some hypothetical product that might have infinitely high fixed costs. The intuition behind assumption 2 is that some products are extremely popular, and dropping them would lead to a large change in variable profits of a manufacturer, while some products are niche or purchased by only some consumers, and adding them would lead to a small change in variable profits.

Every time a upper (lower) bound of fixed costs is missing, I can replace it with the highest (lowest) change in variable profit from dropping (adding) a product from the same brand. Replacing missing bounds this way should give me fixed cost bounds that are wide enough to contain the true fixed costs.

A discussion on fixed costs: The fixed costs I estimate are static in nature. They are intended to capture the period-by-period costs that a manufacturer has to pay to *continue offering products that already exist.* Some of the important sources of these costs are inventory management, marketing expenses for each product (physician detailing), and the cost of training new sales representatives on programming an ICD. These costs are largely incurred at the hospital level, which justifies my assumption that fixed costs for a product are linear in the number of hospitals that purchase it.

When a manufacturer first introduces a product, they also incur a sunk cost. Some of these costs are the costs of innovation, the costs of applying for FDA approval, and the costs of training sales representatives about a new ICD for the first time. Manufacturers are likely to have dynamic considerations when they decide whether or not to incur these sunk costs, and I am unable to estimate them with my static framework. I circumvent this issue by holding the products that were first introduced during my period of analysis fixed in the counterfactual, i.e. I assume that these new products would still be introduced under a uniform pricing counterfactual. Then the sunk costs of introducing these new products are irrelevant, as they would always cancel each other out when I estimate welfare gains or losses from a uniform pricing policy. It is a reasonable assumption to make in light of my research question, which asks whether manufacturers would delay phasing out their older products under a uniform pricing policy. Moreover, I would always have to hold some products fixed due to computational reasons. In this sense, my model is only able to predict the short run effects of uniform pricing, as in the long run one would expect that uniform pricing would also affect dynamic incentives to innovate.

5 Estimation

5.1 Demand and marginal cost parameters

On the demand side, the following parameters are estimated: $\beta = \{\beta_{bh}, \beta_{year}, \beta_p, \beta_{\mathbf{x}}\}$, and $\sigma = \{\sigma_c, \sigma_p, \sigma_{\mathbf{x}}\}$, where $\beta_{\mathbf{x}} = \{\beta_{MRI}, \beta_{dualchamber}, \beta_{DF4}\}$, and $\sigma_{\mathbf{x}} = \{\sigma_{MRI}, \sigma_{dualchamber}, \sigma_{DF4}\}$. I set $\sigma_{dualchamber}$ and σ_{DF4} to zero. The marginal cost parameters, $\gamma_{\mathbf{z}}$ are also estimated in this stage.

The contraction mapping described in Berry et al. (1995) helps create moment conditions that are used to estimate demand parameters. I also use the first order conditions (FOCs) of the manufacturers to generate additional moment conditions. The first order condition of a manufacturer f's profit function with respect to the price of product j in hospital h at time t is

$$\frac{d\pi_{ft}}{dp_{jht}} = \sum_{h \in H} s_{jht}(\mathbf{p}) M_{ht} + \sum_{h \in H} \sum_{k \in J_{fy}} (p_{kht} - c_{kht}) * \frac{ds_{kht}}{dp_{jht}} M_{ht} = 0$$

For each market (denoted as ht), all the FOCs can be written in matrix form as

$$\mathbf{p_{ht}} - \mathbf{c_{ht}} = -\Delta_{ht}^{-1} \mathbf{s_{ht}}(\mathbf{p}) \tag{5}$$

where $\Delta_{ht}^{jj} = \frac{ds_{jht}}{dp_{jht}}$, and $\Delta_{ht}^{jk} = \frac{ds_{kht}}{dp_{jht}}$ if j and k are owned by the same manufacturer, and 0 otherwise.

The functional form for marginal costs in equation (2) can be plugged into equation 5 above, which creates additional moment conditions, which are then solved using two-step GMM.

I use the PyBLP package described in Conlon and Gortmaker (2020) to estimate demand and marginal cost parameters.

Identification: A key identification assumption here is that manufacturers observe demand and marginal cost shocks after they choose their product offerings. I use the following BLP-style instruments to deal with the endogeneity of prices: the fraction of total ICDs that are dual chamber and purchased from a rival, fraction of total ICDs that are MRI-safe and purchased from a rival, the fraction of total ICDs that are DF4 and purchased from a rival. Similar to Eizenberg (2014), I also interact product characteristics with time and use these as instruments.

The coefficients on the characteristics $\beta_{\mathbf{x}}$ are identified using within brand-hospital substitution between characteristics. It is possible to identify these coefficients because a single brand can have MRI-safe and MRI-unsafe versions, single and dual chamber versions, and DF-4 and non-DF-4 versions.

Marginal cost parameters are identified through the correlations between marginal costs backed out from the markup equation with ICD characteristics.

5.2 Fixed costs

In this stage of the analysis, fixed cost bounds for each brand are estimated. Recall, that

$$\frac{F_{jy}}{H_{jy}} = F^b + \eta_{jy}$$

The upper bound of fixed costs, $\bar{F}_{jy}$ can be estimated for each product j observed in the data in year y. The steps for the estimation are as follows:

1. Draw n times from estimated distributions of ξ and ω.

2. For each draw d, compute equilibrium and calculate $VP_{fy}(J_{fy}, J_{-fy}|\xi^d, \omega^d, \beta, \gamma, \sigma)$. J_{fy} is the set of product offerings at the observed equilibrium.

3. Drop product j in year y, and re-compute equilibrium. Calculate $VP_{fy}(J_{fy}\backslash j, J_{-fy}|\xi^d, \omega^d, \beta, \gamma, \sigma)$ for each draw.

4. $F_{jy} \leq 1/n \sum_{d=1}^{n}[VP_{fy}(J_{fy}, J_{-fy}|\xi^d, \omega^d, \beta, \gamma, \sigma) - VP_{fy}(J_{fy}\backslash j, J_{-fy}|\xi^d, \omega^d, \beta, \gamma, \sigma)]$

The lower bound of fixed costs $\underline{F}_{j\prime y}$, for a product $j\prime$ **not** observed in the data in year y is estimated as follows:

1. Draw n times from estimated distributions of ξ and ω.

2. For each draw f, compute equilibrium and calculate $VP_{fy}(J_{fy}, J_{-fy}|\xi^d, \omega^d, \beta, \gamma, \sigma)$. J_{fy} is the set of product offerings at the observed equilibrium.

3. Add product $j\prime$ in year y, and re-compute equilibrium. Calculate $VP_{ft}(J_{fy}{\cup}j\prime, J_{-fy})|\xi^d, \omega^d, \beta, \gamma, \sigma)$ for each draw.

4. $F_{j\prime y} \geq 1/n \sum_{d=1}^{n}[VP_{fy}(J_{fy} \cup j\prime, J_{-fy})|\xi^d, \omega^d, \beta, \gamma, \sigma) - VP_{fy}(J_{fy}, J_{-fy}|\xi^d, \omega^d, \beta, \gamma, \sigma)]$

My setting poses a complication: all products do not enter the choice sets of all hospitals in each year. Therefore, while estimating lower bound of the fixed cost of a product in a year, I have to make an assumption about which hospitals' choice sets a product $j\prime$ would enter if it were offered in year y. I assume that if a hospital was buying $j\prime$ within a year of its exit, it would enter the choice set of that hospital if it were re-introduced in year y.[20]

After I estimate the upper or lower bound of fixed costs for each product-year, I apply

[20]I do robustness around this assumption; changing it to 2 years does not change my estimated bounds significantly.

Eizenberg (2014)'s solution to the problem of selection. I outlined the potential sources of period-by-period fixed costs in the previous section; most of these are incurred at the hospital level. Hence, we can think of an estimated fixed cost bound for a product as an aggregated fixed cost over all the hospitals that had this product in their choice set. I report fixed cost bounds as a hospital level average, and whenever an upper (lower) bound is missing, I replace it with the highest (lowest) estimated hospital level average upper (lower) bound. Then, I take an average over all the upper bounds to get (per hospital) $\bar{F}^b$, and an average over all lower bounds to get (per hospital) $\underline{F}^b$.

6 Results

Table 2 displays the demand estimates and second stage cost estimates.[21] The first column reports β_c, β_p and β_x, and we can see that the β_p is positive, implying that agents have a disutility for price. The average preferences for product characteristics are consistent with our intution; agents prefer MRI-safe ICDs to MRI-unsafe ones, they prefer Dual Chamber ICDs to Single Chamber ones, and they prefer DF4 ICDs to non-DF-4 ones.

The random coefficients on the constant, prices, and MRI-safe status are large, which confirms that there is a lot of heterogeneity in the agents' preferences for the inside option, prices and the MRI-safe feature. In table 3, in which average elasticities over products, hospitals and time, for the most popular brands of the two largest manufacturers in my data have been reported by MRI-safety type.[22] Columns (2)-(5) report the percent change demand for the row product for a 1% increase in prices of the column product. The cross price elasticities are consistent with our intuition: 1) consumers of MRI-safe (MRI-unsafe) ICDs have higher substitution to other MRI-safe (MRI-unsafe) ICDs and 2) There is higher within-firm substitution than between-firm substitution.

[21]See table 11 in appendix A.4 for logit results

[22]See table 12, 14 and 13 in appendix A.4 for the diversion table, and the full elasticities and diversion matrices.

Average marginal cost (γ) estimates are reported in the third column of table 2. Implied average marginal costs are in table 4. On an average, MRI-safe ICDs have a marginal cost of about $550 more for manufacturers than MRI-unsafe ICDs of the same device type. Dual Chamber devices have an average marginal cost of about $1,100 more than Single Chamber devices with the same MRI-safe status. At first glance, marginal costs might seem high, but manufacturing costs are not the only component of marginal costs incurred by manufacturers. Sales representatives are on the payroll of device manufacturers and are an integral part of each implant process; they help physicians choose a product, are often present in the operating room when the implant actually takes place, and help with post-implant technical issues.[23] Further, quality control for each device and the risk of lawsuits due to device malfunctions and/or recalls add to the expected economic marginal cost of each ICD.

Table 5, reports $\bar{F}^b$ and $\underline{F}^b$ of the top selling brand (the brands in table 1) of the two largest manufacturers in my data, Medtronic and St Jude Medical. 95% confidence intervals of these bounds were estimated using the method in Imbens and Manski (2004). The confidence intervals widen the fixed cost bounds. Fixed costs are a substantial fraction of average revenues from each hospital. If we assume that the true fixed costs are the midpoint of the estimated upper and lower bounds, then in 2019, the average fixed cost for a product in a hospital accounted for 19.2% (Medtronic) and 25% (St Jude Medical) of average revenues from a hospital.

[23]https://www.epstudiossoftware.com/device-reps-and-patient-care-an-inconvenient-truth/

Table 2: Demand estimates

	β	σ	γ
-(Prices)	1.7	0.41	
	(0.30)	(0.25)	
MRI-safe	0.67	1.03	0.24
	(0.07)	(0.24)	(0.16)
Dual Chamber	0.84		0.17
	(0.11)		(0.07)
DF-4	0.27		-0.06
	(0.02)		(0.04)
Constant	0	5.3	-0.14
		(1.2)	(0.15)

This table has demand and marginal cost estimates. The first column (β) has average estimates, the second column (σ) has the standard deviations of the random coefficients, and the third column (γ) has the marginal cost coefficients.
The price coefficient is assumed to follow a lognormal distribution. The random coefficient on MRI-safe status and the constant is assumed to be normally distributed.

Table 3: Price elasticities

			Medtronic		St Jude Medical	
		(1)	(2)	(3)	(4)	(5)
	MRI-safe	Own	MRI-unsafe	MRI-safe	MRI-unsafe	MRI-safe
Medtronic	MRI-unsafe	-5.03	0.65	0.81	0.39	0.33
	MRI-safe	-4.94	0.43	1.04	0.27	0.43
St Jude Medical	MRI-unsafe	-4.82	0.62	0.73	0.51	0.53
	MRI-safe	-4.41	0.29	0.92	0.29	0.65

This table is the mean elasticities matrix for products of the most popular brand from the top 2 firms in my data, averaged over hospitals, products and time. The MRI-safe products are in the gray regions of the table. Column (1) reports average own price elasticities, while columns (2)-(4) report average cross price elasticities Each element from columns (2)-(5) reports the % change in the row variable from a 1% increase in price of the column variable

Table 4: Marginal cost estimates

Devicetype	MRI-safe	Marginal cost estimates	Prices
Dual Chamber	No	8,406	12,986
Dual Chamber	Yes	8,944	14,116
Single Chamber	No	7,281	11,363
Single Chamber	Yes	7,855	12,771

This table reports average estimated marginal costs from the BLP estimation and average prices from the data. Averages are calculated using data after 2015, as the first MRI-safe ICD was approved in late 2015. Prices and marginal costs are in dollars.

Table 5: Fixed cost bounds (per hospital)

Brand	Estimates $\underline{F}^b$	Estimates $\bar{F}^b$	95% Confidence Intervals $\underline{F}^b$	95% Confidence Intervals $\bar{F}^b$
Medtronic	22,951	34,657	21,493	37,118
St Jude Medical	15,571	18,615	14,871	19,927

This table displays $\underline{F}^b$ and $\bar{F}^b$ for the top brands of Medtronic and St Jude Medical, which are the two largest firms in my data. These estimates account for selection using the method in Eizenberg (2014). 95% confidence intervals are estimated using Imbens and Manski (2004). Fixed costs are in dollar amounts.

7 Counterfactual

7.1 Description

I answer the following research question: Suppose manufacturers are forced to charge the same price for the same product in all hospitals, would they delay phasing out their older, lower quality and cheaper products, and use them to indirectly price discriminate? How would this affect consumer welfare and the take-up of newer and better technologies?[24]

In the counterfactual analysis, I impose that in each time period t, manufacturers must set the same price for the same product across all hospitals (uniform pricing). I draw from the estimated distribution of ξ_{jht} and ω_{jht} and I use my estimated demand parameters, marginal cost parameters, and fixed cost bounds to compute the potential equilibria under this uniform pricing assumption.

Each potential equilibrium for year y is a set of product offerings, and the expected prices and shares for this set of product offerings. A set of product offerings can be visualized as a $J_y \times 1$ vector, where J_y is the number of all products that existed during 2014-y, regardless of whether or not they were offered. If product j is offered, then the jth element of this vector will take a value 1, and 0 otherwise. If J_y products existed from 2014-2019, 2^{J_y} such vectors are possible.

[24] See appendix A.1 for an illustrative model.

For each possible vector of product offerings, calculating prices and shares under a uniform pricing equilibrium is equivalent to modifying the profit function for each manufacturer, i.e.,

$$\pi_{fy} = \underbrace{\sum_{t=1}^{2} \sum_{h \in H_{jt}} \sum_{j \in J_{fy}} (p_{jt} - c_{jht}) s_{jht}(\mathbf{p}) M_{ht}}_{\text{Variable profits } VP_{fy}} - \sum_{j \in J_{fy}} F_{jy} \tag{6}$$

Equation (6) is different from equation (1) because prices in equation (6) are p_{jt}, assumed to be the same for a product j at time t across all hospitals.

From these 2^{J_y} possible vectors, I can find the vectors that cannot be ruled out as potential equilibria, i.e. the set of vectors which exist as equilibria for *some fixed costs within the estimated intervals* under a uniform pricing regime. I cannot conclusively determine which equilibrium would actually hold, because fixed costs are only partially identified. In the counterfactual analysis, I follow Eizenberg (2014) and set η_{jy} to zero. Ideally I would like to estimate the distribution of η_{jy}, draw from this distribution and then use F_{jy}, but that is beyond the scope of my paper. However, I have not put any structure on η_{jy}. [25]

I find the set of potential equilibria by checking whether each of the 2^{J_y} vectors of possible product offerings is an equilibrium for some fixed cost values within the estimated intervals. For each vector, I do this in two steps. First, I check if any manufacturer has a single profitable deviation from this vector, i.e. holding all other product offerings constant, could any manufacturer vary one product from this set of offerings and increase its total expected profits, where the expectation is over ξ and ω.[26] I use this method to eliminate vectors that have a profitable deviation. Second, for the subset of vectors that survived

[25] This is unlike Ciliberto et al. (2018) and Fan and Yang (2020b), which estimate the distribution of η_{jt} and draw from it in the counterfactual.

[26] Here is a simplified example: Suppose $J = 6$, and there is a single manufacturer f that owns all these products, which all belong to brand b. Suppose the vector of product offerings that I am checking is (0,1,0,0,0,0). Calculate expected variable profits of the manufacturer at this vector. Then calculate expected variable profits at the following deviation: (1,1,0,0,0,0). If the increase in the expected variable profits from adding product 1 is higher than $\bar{F}^b$, it is a profitable deviation. If it is is not, then check the second possible deviation, i.e (0,0,0,0,0,0). If the decrease in expected variable profits from dropping product 2 is lower than $\underline{F}^b$, it is a profitable deviation. If not, I check the third deviation and so on

step 1, ensure that there is a non-empty set of fixed cost values within the estimated bounds for which this equilibrium would exist.[27]

Allowing manufacturers to vary all products in the counterfactual analysis would be computationally impossible. With J products there are 2^J possible vectors that have to be put through the two steps described above. During the six-year period of my data, a total of 68 products were offered. 2^{68} is about 2.95×10^{20} potential vectors, which are impossible to go through. I make the following assumptions to reduce the computational burden of this problem:

- I restrict my counterfactual analysis to 2019. This is because the second-largest manufacturer in my data gained FDA approval for its MRI-safe devices in late 2017, and almost all MRI-unsafe ICDs produced by all 3 manufacturers were phased out by the end of 2018. This makes 2019 an appropriate year for the counterfactual, as I can answer the question of whether manufacturers would have continued offering some MRI-unsafe ICDs under uniform pricing.
- I restrict the set of products that can be varied in the counterfactual.
  - First, of the three manufacturers in my data, I allow only the top two manufacturers in my data to vary their product offerings.[28] These top two manufacturers capture about 90% of total purchase volumes in my data.
  - Second, I allow each of these 2 manufacturers to vary products only from their most popular brand. These top 2 brands from the 2 manufacturers account for 66% and 60% of the total ICD sales by each manufacturer in 2019.

[27] I want to highlight the importance of this with the following simplified example: Suppose $J = 6$, and there is a single manufacturer f that owns all these products, which all belong to brand b. Suppose a vector that survives step 1 is: (1,1,0,0,0,0). Now it is possible that in this equilibrium, product 1 can be offered for fixed cost values in the interval [a,b], while product 2 can be offered for fixed cost values in interval [c,d]. If these two intervals do not overlap, then this equilibrium cannot hold, and this vector should be dropped.

[28] The top 2 manufacturers in my data aren't necessarily the top 2 manufacturers overall, as hospitals faced a disclosure issue with Boston Scientific, as explained in footnote 11.

- I drop products that exited before the end of 2015.
- I only allow manufacturers to delay the exit of older products that are not MRI-safe. More than 90% of products that exit before 2019 are MRI-unsafe. Further, my research question is about whether manufacturers would delay the exit of older technologies under uniform pricing, so this is a fair assumption.
- I only allow manufacturers to vary products that sold more than 500 units in at least one year when they were offered.

After making all the simplifying assumptions above, I am left with 8 products that 2 manufacturers are allowed to vary in 2019 under a uniform pricing counterfactual. None of these 8 products were offered in 2019, and none of them were MRI-safe. 3 of these products belonged to St Jude Medical and 5 belonged to Medtronic.

7.2 Results

I generate three sets of results: First, I re-estimate the price discrimination equilibrium for 100 ξ_{jht} and ω_{jht} draws, and find manufacturers' expected prices, shares, expected variable profits, and hospital surplus under the observed product offerings.[29] Second, I keep product offerings fixed at the observed set, impose that manufacturers must do uniform pricing, and estimate the equilibrium for the same 100 ξ_{jht} and ω_{jht} draws. Finally, I allow manufacturers to delay the exit of the 8 MRI-unsafe products described in the previous subsection and under uniform pricing, I solve for all possible equilibria that exist given my estimated fixed cost intervals.

In each case, hospital (consumer) surplus for a market (hospital h at time t) in 2019

[29]It is important to re-estimate the price discrimination equilibrium for 100 ξ_{jht} and ω_{jht} draws and use these outcomes as a relevant comparison to the uniform pricing case, rather than using the observed outcomes from the data. This is because the prices, shares, profits and welfare observed in the data occur for a particular realization of ξ_{jht} and ω_{jht}, while the object we are interested in is the expected values of these outcomes before each manufacturer takes their entry decision.

is as follows:

$$CS_{ht} = [\frac{1}{1000}\sum_i \frac{log(1+\sum_j exp(V_{ijht}))}{\beta_p^i}]M_{ht}$$

where M_{ht} is the market size of hospital h at time t. V_{ijht} is the indirect utility that simulated i consumer gets from product j in time t at the equilibrium price, and β_p^i is the value of the random coefficient on price for consumer i. I simulate 1000 physician-patient pairs, so I divide the expression in brackets by 1000 to get average surplus for a consumer in a market.

7.2.1 Results without product entry

Figure 3 shows that if we kept product offerings fixed, expected prices for each product under a uniform pricing counterfactual would be higher than the median expected prices under price discrimination. There is some degree of heterogeneity in strategies between manufacturers; Biotronik, which has the lowest market share of all 3 manufacturers in my data would target its highest willingness-to-pay consumers by always setting its uniform prices above the 75th percentile of expected prices under price discrimination. Medtronic and St Jude Medical also price to their inelastic consumers, but they do so to a lesser degree. The shares version of this figure can be found in figure 8 in appendix A.4.

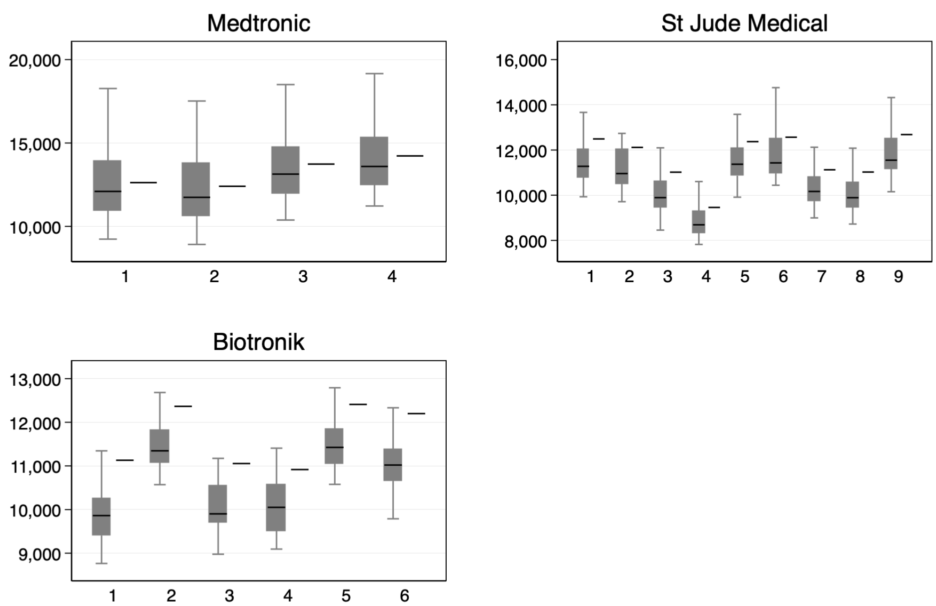
Panel A of table 6 shows that keeping product offerings fixed, the higher prices under uniform pricing cause a reduction in the average inside good share by 15.7% (row 5). Thus, variable profits of Medtronic and St Jude Medical to drop by 9% and 3.1% (row 1) respectively, and there is a loss in expected hospital surplus of 5.2% (row 2). Row 5 compares total surplus under uniform pricing, calculated as the sum of Medtronic's variable profits, St Jude Medical's variable profits and hospital surplus, to total surplus under price discrimination. Total surplus under uniform pricing drops by 6.1%: a result that is driven by the drop in both variable profits and hospital surplus.

My results are consistent with Grennan (2013), who finds that when hospitals are price takers, there is a reduction in competition under uniform pricing, and manufacturers choose to price to their more captive markets, which increases prices, and lowers hospital surplus and manufacturer profits. Grennan (2013) finds that hospitals would need to have large increases in their bargaining abilities for them to have welfare gains from uniform prices. In the next section, I show that even when hospitals are price takers, they could have welfare gains under uniform pricing, as manufacturers would indirectly price discriminate by delaying the exit of some of their older, cheaper products. This would 1) increase product variety, and 2) increase competition from the presence a rival's cheaper product, which would lower expected prices relative to the case of uniform pricing with fixed product offerings. Both of these forces would offset the welfare losses from the higher expected prices under uniform pricing.

7.2.2 Results with product entry

Next, holding current product offerings fixed, I allow the two largest manufacturers in my data to delay the exit of eight MRI-unsafe products from their top brands (see section 7.1 for a recap). I find the set of equilibria that would exist for some fixed cost values in my estimated bounds. Three potential equilibria exist. Panel B from table 6 reports the results from these three equilibria. Under uniform pricing, the current set of product offerings is ruled out as a potential equilibrium; at least one of these 8 products, and a maximum of two products, one of each manufacturer, would continue to be offered in 2019. Row 2 in panel B shows the set of fixed cost values for each manufacturer for which that equilibrium would exist. Equilibria 1 and 2 exist only for a narrow range of fixed cost values of products belonging to St Jude Medical's top brand, while Equilibrium 3 exists for the largest range of fixed costs in my estimated bounds. Thus, given my estimated bounds, my "preferred" equilibrium is Equilibrium 3, in which manufacturers would delay

Figure 3



This figure shows the expected prices of the products that were offered in 2019 under price discrimination and uniform pricing. The x-axis has products, and the y axis has prices. For the price discrimination case, the upper hinge of the box is the 75th percentile of prices, and the lower hinge is the 25th percentile of prices, averaged for the two periods in 2019. For the uniform price case, manufacturers charge the same price in all hospitals in each period, so there is one price for each product-period. I report the average over the two periods in 2019.

Table 6: Counterfactual analysis

A: No product entry [a]	Price Discrimination	Uniform prices	
1.Expected variable profits (million $)			
Medtronic	67.8	61.7	
Δ (%)		**-9.0**	
St Jude Medical	25.9	25.1	
Δ (%)		**-3.1**	
2. Expected hospital surplus (million $)	137.2	130.0	
Δ (%)		**-5.2**	
3. Δ Expected total surplus (%)		**-6.1**	
4. MRI-safe ICD share	0.98	0.98	
Δ (%)		**0**	
5. Average inside good share	0.19	0.16	
Δ (%)		**-15.7**	
B: Allowing product entry under uniform prices [b]	Equilibrium 1	Equilibrium 2	Equilibrium 3
1. # Products re-entering	1	2	2
Medtronic	1	1	1
St Jude Medical	0	1	1
2. Fixed cost interval $[\underline{F}^b, \bar{F}^b]$ **($10,000s)**			
Medtronic	[2.30, 3.47]	[2.30, 3.47]	[2.30, 3.47]
St Jude Medical	[1.83, 1.86]	[1.57, 1.57]	[1.56, 1.83]
3. Expected variable profits (million $)			
Medtronic	68.5	66.3	65.5
St Jude Medical	23.6	26.4	27.8
4. Δ Expected total profits (%)			
Medtronic	**[-8.1,-4.9]**	**[-11.3, -8.3]**	**[-12.5, -9.4]**
St Jude Medical	**-8.8**	**[-8.8, -8.8]**	**[-8.8, -6.6]**
5. Expected hospital surplus (million $)	135.2	139.7	141.9
Δ (%)	**-1.4**	**1.8**	**3.4**
6. Δ Expected total surplus (%)	**[-4.2,-3.4]**	**[-3.2, -2.3]**	**[-2.6,-1.5]**
7. MRI-safe ICD share	0.87	0.81	0.79
Δ (%)	**-11.2**	**-17.3**	**-19.3**
8. Average inside good share	0.17	0.17	0.18
Δ (%)	**-10.5**	**-10.5**	**-5.2**

[a] Panel A of this table reports expected variable profits of the two firms whose products I vary, expected hospital surplus, changes in total surplus, MRI-safe ICDs as a fraction of total inside good sales, and the average inside good shares under (1) price discrimination and (2) uniform pricing without product entry. Percentage differences relative to the price discrimination case are reported in bold.

[b] Panel B of this table reports results for each potential equilibrium under uniform pricing. The number of products that re-enter, the values of per hospital fixed costs of each manufacturer's most popular brand for which each equilibrium will hold are reported, expected variable profits of the two firms whose products I vary, change in total profits relative to the price discrimination case, expected hospital surplus, MRI-safe ICDs as a fraction of total inside good sales, expected hospital surplus, and average inside good share are reported for each case. Percentage differences relative to the price discrimination case are reported in bold.

In each case, Δ total surplus is relative to the price discrimination case. Biotronik is excluded from the total surplus calculation.

Expected profit and surplus measures are reported as a sum of the two periods in 2019.

Table 7: Average estimated prices

Firm	MRI-safe	No entry		With entry		
		Price Discrimination (1)	Uniform Prices (2)	Equilibrium 1 (3)	Equilibrium 2 (4)	Equilibrium 3 (5)
Medtronic	No			11,717	11,501	11,352
	Yes	13,554	13,735	13,874	13,765	13,688
	Yes	14,054	14,226	14,377	14,266	14,195
St Jude Medical	No				9,051	
	No					10,293
	Yes	10,441	11,024	10,899	11,007	11,029
	Yes	11,848	12,489	12,335	12,416	12,455
	Yes	12,160	12,565	12,483	12,562	12,569

This table displays average prices under price discrimination (col 1), uniform prices without endogenous products (col 2), and uniform prices in the 3 equilibria with endogenous products (cols 3-5)
The MRI-safe products are in the gray region of the table
The averages in the price discrimination case are average estimated prices over all hospitals and two time periods in 2019, and the averages in the uniform pricing case are average estimated prices over the two time periods in 2019

phasing out a total of two MRI-unsafe products, one by each manufacturer.

The hospital surplus effects of keeping these additional MRI-unsafe products are ambiguous. First, the increase in product variety would directly increase hospital surplus. Second, a manufacturer which keeps its older, lower quality (MRI unsafe) products around for longer may use them to indirectly segment its markets by setting higher prices for its newer, higher quality (MRI-safe) products. This would put a downward pressure on hospital surplus. Third, an additional product offered by a manufacturer's rival would have a competition effect, which would work to lower the prices of the manufacturer's products, increasing hospital surplus. The second and third mechanisms can be seen table 7, which shows average expected prices of products of the top brands of Medtronic and St Jude Medical under each scenario. Average expected prices in the price-discrimination case (column 1) are always lower than those in the uniform pricing case with fixed product offerings (column 2). When firms are allowed to vary their product offerings, in equilibrium 1 (column 3), in which only Medtronic keeps its older product on the shelves for longer, the average expected prices for all of Medtronic's MRI-safe products increase (the indirect price discrimination effect), while those of St Jude Medical's products decrease (the competition effect). In equilibria 2 and 3 (columns 4 and 5), in which both manufacturers keep an older product on their shelves, the competition effect outweighs the indirect price discrimination effect, and average expected prices of MRI-safe ICDs under these equilibria are almost equivalent to average expected prices under uniform pricing with fixed product offerings.

In equilibrium 1, the losses to hospital surplus (row 5 of table 6) due to uniform pricing are partially offset by Medtronic's additional MRI-unsafe ICD. Under equilibria 2 or 3, expected hospital surplus under uniform pricing is higher than the price discrimination case by up to 3.4%. Thus, under uniform pricing, even though manufacturers would price their existing products to target their inelastic markets, they would also delay phasing out products equipped with an older technology so that they can use these products to target their more elastic markets. While this would cause an increase in hospital surplus, the share of ICDs purchased that are equipped with a superior technology would drop by up to 19.3% (row 7 of table 6).

In each equilibrium, the change in expected total profits (row 4) for a manufacturer, relative to the price discrimination case depends on the change in variable profits in that equilibrium and if an additional product is offered, the fixed costs of offering it. I find that when both manufacturers continue to offer an MRI-unsafe product, expected total profits of manufacturers are even lower than they would be under uniform prices with fixed product offerings. This is because it is optimal for a manufacturer to continue offering an MRI-unsafe product, *given the other manufacturer's decision to continue to offering one*. The business stealing effect from a rival's entry, the added fixed cost of entry, and the inability of manufacturers to fully recover the consumers that were lost due to the higher prices under uniform pricing (row 8) lead to lower profits for both manufacturers.

Row 6 in panel B shows the percentage difference in expected total surplus under uniform pricing, relative to the price discrimination case. Expected total surplus under uniform pricing is lower than the price discrimination case by 1.5%-4.2% (row 6).

8 Conclusion

Many papers that study the effects of third-degree price discrimination (or market segmentation) assume that the alternative to third-degree price discrimination is no price discrimination. I use the context of a specific type of implantable medical device to show that in the absence of third-degree price discrimination, manufacturers can use products that are vertically differentiated in quality to indirectly price discriminate. They would do so by keep their older, cheaper products on the shelves for a longer period to target their more elastic consumers, while raising the prices of their newer, higher quality products to target their inelastic consumers. Grennan (2013) studies the industry for a different type of implantable medical device to show that hospitals would need large increases in their bargaining abilities to benefit from uniform pricing. I show that even if hospitals were price takers, the delayed exit of older products would offset the expected hospital welfare losses from the higher prices due to uniform pricing. In the equilibrium that exists for all values of fixed costs in my estimated intervals, expected hospital surplus would be higher than the price discrimination case (a reversal of the predictions from uniform prices with fixed product offerings). However, under these equilibria more patients would be implanted with older, inferior devices. On the manufacturers' side, given that a rival is continuing to offer an older product, it is optimal for a manufacturer to also continue offering an older product, but this leads to lower profitability than they would have if product offerings were fixed.

My results highlight the importance of accounting for endogenous product offerings while analyzing the policy question of whether third-degree price discrimination or uniform pricing is better for consumers. The answer does not just depend upon how manufacturers will price in the absence of price discrimination, but also on how they will change their product offerings.

My results have some caveats. First, to my knowledge, there is no evidence that changing the costs of medical devices would pass through to patients. Medicare reimburses hospitals for an entire implant procedure, and doesn't account for the price that the hospital actually paid for the device. Thus, any welfare gains and losses should be interpreted as those of a hospital. Second, physicians are known to have brand loyalties in this industry. I have not accounted for brand loyalty in my demand estimation. I expect elasticities to drop when I do so. Third, I show in appendix A.3 that quantity discounts do exist in this industry, although they account for a small fraction of total variation in prices. I have not modeled quantity discounts explicitly in my analysis. Finally, in my counterfactual, I hold existing product offerings fixed and allow manufacturers to continue offering their older products that were already phased out. It is possible that manufacturers would change their mix of MRI-safe and MRI-unsafe ICDs in a uniform pricing counterfactual. I hope to address some of these caveats in future iterations of this paper, and leave the rest to future work.

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A Appendix

A.1 An illustrative model

In this section I will illustrate the intuition for my research question with a simple theoretical model. We will examine a hypothetical economy under 3 cases: 1) manufacturers are allowed to price discriminate, 2) manufacturers are not allowed to price discriminate and there is no product entry, and 3) manufacturers are not allowed to price discriminate and there is product entry.

Let us assume that the whole economy has two segmented markets. Each market has 1 consumer, indexed 1 and 2 for the two markets. Let us assume that there is one manufacturer that is currently selling a product H. This single manufacturer assumption rules out some of the mechanisms discussed in the paper, but is necessary for this model to derive simple predictions and provide clarity along other dimensions. The fixed cost of keeping H in the market is F, and the marginal cost of selling each unit of H is c.

The utility that consumer i gets from buying product H is :

$$U_i = \theta_i - p_i^H$$

where p_i^H is the price of product H faced by consumer i. Without loss of generality, let us assume that $\theta_2 > \theta_1$

Case 1: Price Discrimination

In this scenario manufacturers are allowed to third degree price discriminate.[30]

$$p_1^H = \theta_1$$

$$p_2^H = \theta_2$$

The manufacturer seeks to extract all the surplus from the two consumers (markets), and hence consumer surplus $= 0$.

[30] In this example, third-degree and first degree price discrimination mean the same thing because of the single-consumer market assumption.

Firm profits under this case are:

$$\pi_{c1} = \theta_1 + \theta_2 - 2c - F$$

$$p_1^H = \theta_1$$

$$p_2^H = \theta_2$$

The manufacturer seeks to extract all the surplus from the two consumers (markets), and hence $CS_{c1} = 0$, where CS_{c1} is consumer surplus in case 1.

Firm profits under this case are:

$$\pi_{c1} = \theta_1 + \theta_2 - 2c - F$$

Case 2: Uniform prices without product entry

In this scenario manufacturers must charge the same price for the same product in all markets (to all consumers). I assume that manufacturers cannot introduce or remove products in this case.

There are 2 possibilities for a manufacturer's optimal pricing strategy:

Case 2.1

$$p_1^H = p_2^H = p_{c21} = \theta_{\mathbf{2}}$$

$$\pi_{c21} = \theta_2 - c - F$$

$$CS_{c21} = 0$$

In this sub-case, consumer 1 will not buy the product, as $\theta_2 > \theta_1$. All of consumer 2's surplus will be extracted by the manufacturer, so consumer surplus, $CS_{c21} = 0$.

Case 2.2

$$p_1^H = p_2^H = p_{c22} = \boldsymbol{\theta_1}$$

,

$$\pi_{c22} = 2(\theta_1 - c) - F$$

$$CS_{c22} = \theta_2 - \theta_1$$

In this sub-case, both consumers will buy the product, but consumer 2 will pay a price lower than their willingness to pay, and this will lead to positive consumer surplus.

Case 2.1 will occur if:

$$\pi_{c21} \geq \pi_{c22} \implies c \geq 2\theta_1 - \theta_2$$

The further θ_1 and θ_2 are from each other, the more likely is *Case 2.1* to occur. Thus, if preferences between markets are heterogenous, then under a uniform pricing scenario, the manufacturer will be more likely to price to the higher end (more inelastic) markets. This is the intuition behind the results in Grennan (2013).

Case 3: Uniform prices with product entry

Now suppose a manufacturer has the option of introducing a new product, L. For simplicity, let us assume that the fixed cost of doing so is F and marginal cost of selling each unit is c (the costs have the same magnitudes as H).

The utility that consumer i gets from buying L is:

$$U_i = \phi\theta_i - p_i^L$$

where ϕ<1.

A separating equilibrium in which consumer 1 buys L and consumer 2 buys H is possible. Then:

$$p_L = \phi\theta_1$$

The IC for consumer 2 will give us p_H, i.e.

$$\phi\theta_2 - p_L \leq \theta_2 - p_H$$

$$\implies p_H \leq \theta_2 - \phi(\theta_2 - \theta_1)$$

$$\pi_{c3} = (\theta_2 - \phi(\theta_2 - \theta_1) - c - F) + (\phi\theta_1 - c - F)$$

$$CS_{c3} = \phi(\theta_2 - \theta_1)$$

Now, suppose Case 2.1 holds under uniform pricing without entry, i.e manufacturers charge at the higher end (to the inelastic parts of the demand curve). Then, a manufacturer will introduce product L if

$$\pi_{c3} \geq \pi_{c21}$$

$$\implies F \leq \phi(2\theta_1 - \theta_2) - c$$

If L enters, consumer surplus $= \phi(\theta_2 - \theta_1)$, and thus product entry is better for consumer welfare.

On the other hand, if Case 2.2 holds under uniform pricing, i.e. if the manufacturer chooses to price at the lower end under the uniform pricing counterfactual, product entry can worsen consumer surplus relative to the case without product entry, as it might cause the manufacturer to indirectly segment its markets through the separating equilibrium described above. Product entry will occur if:

$$\pi_{c3} \geq \pi_{c22}$$

$$\implies F \leq (1-\phi)(\theta_2 - 2\theta_1)$$

If L enters, $\phi(\theta_2 - \theta_1) \leq (\theta_2 - \theta_1)$, which implies that product entry is worse for consumer welfare.

Thus, the main takeaways from this model are that:

- Under uniform pricing, manufacturers will introduce new products if fixed costs of entry are low enough.
- Product entry may or may not improve consumer welfare.

A.2 Data cleaning for demand estimation

My raw data has monthly purchases and prices of ICDs by 868 hospitals from 2014-2019.[31] These prices are inclusive of rebates and any other discounts, and are the prices that these hospitals actually pay to the manufacturers. The following steps help me arrive at my final dataset for demand estimation:

- I define a product as a combination of SKU and MRI-safe status. This is because St Jude Medical receives MRI-safe approval for a some of their existing SKUs. I treat such an SKU before it received MRI-safe approval as a separate product from the same SKU after it received MRI-safe approval. I assume that after its approval, St Jude Medical always had an option to market the same MRI-safe ICD as a MRI-unsafe one (as it was doing before it received approval).
- I aggregate the data to a hospital-product-six month period. Prices of the same product are very sticky within hospital over time (see table 8), so this is a reasonable assumption.

[31] I also have data on CRT-D purchases, but I drop these due to the reasons outlined in footnote 12.

- For each manufacturer, I drop products that 1) do not account for the top 80% of their sales 2) have less than 35 products sold in each six month period.

- I drop Boston Scientific and Microport Scientific. Hospitals' purchases from Boston Scientific are under-reported, especially in the early years of my data. This is because Boston Scientific signed confidentiality contracts with many hospitals, which prevented them from disclosing the prices they paid for devices. Under-reporting by Boston Scientific is a common problem across datasets on medical device purchases. Microport Scientific accounts for less than 1% of total ICD sales in my data during this period, so I drop the manufacturer.

- I remove pricing outliers by winsorizing the pricing data at the 99th and 1st percentiles.

- **Market size:** I use the following information to construct an estimate of the market size for each hospital-year.

  - There are medical journal articles that discuss the use of anti-arrhythmiatic drugs as an alternative to ICDs (for example, Abboud and Ehrlich (2016) and Bokhari et al. (2004)). I use Medicare Part-D Prescriber Public Use Files from 2013-2018 to get the annual number of unique beneficiaries for the most popular anti-arrhythmiatic drug. I don't have this data for 2019, so I use the same number for 2019 as I do for 2018.

  - In 2011, 75% of total ICD implants were implanted in the elderly (Kramer et al., 2015). I assume that this percentage does not change substantially during the period of my data.

  - 70% of patients with ICD implants need to also take anti-arrhythmiatic drugs

[32] https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/frequently-asked-questions-

(Bollmann et al., 2005).

- The life-span of an ICD is 5-7 years. [32]
- Another alternative to ICDs is treatment CRT-Ds, which have the ICD function, but also additionally work to re-synchronize the ventricles of the heart.
- GlobalData gave me multiplication factors that let me extrapolate total ICD sales by each manufacturer in the US from my data (which has a sample of hospitals).

I use the above information to form the following estimate of the inside good share:

$$\tilde{s}_y^{ig} = \frac{\sum_f f_f \times 0.75 \times total\_ICD_{fy}}{beneficiaries_y + \sum_f f_f \times 0.75 \times total\_ICD_{fy} - \sum_f f_f \times total\_ICD_{fy} \times 0.75 \times 0.7 \times 6}$$

where f_f is the multiplication factor for firm f from GlobalData, the numerator is an estimate of the total number of ICD implants (including CRT-Ds) in the elderly in the US, and the denominator is the number of unique Medicare beneficiaries for the most popular anti-arrhythmiatic drug (amiodarone), plus the total number of ICD implants (including CRT-Ds) in the elderly, minus the estimated number of patients with ICDs who also were taking amiodarone.

- Note that I drop Boston Scientific from my analysis (i.e. I put it in the outside good). Therefore, I have to account for Boston Scientific market shares while constructing inside good shares. I account for under-reporting by Boston Scientific in the following way:

about-pacemakers-and-implantable-cardioverter-defibrillators-icds

– Reporting for purchases from Boston Scientific increased in 2014-2019. 2018 and 2019 had the highest reporting for Boston Scientific. I assign hospitals that reported purchases from Boston Scientific a s_h^{bsc} = the hospital's share in 2019 (or 2018), where s_h^{bsc} is the estimate share of Boston Scientific in that hospital. I assign the remaining hospitals that do not report purchases from Boston Scientific s_h^{bsc} = aggregate market share of Boston Scientific.

Then, the inside good share is:

$$s_{hy}^{ig} = \tilde{s}_y^{ig} \times (1 - s_h^{bsc})$$

The market size for each hospital-year is $\frac{total\_icd_{hy}}{s_{hy}^{ig}}$, where $total\_icd_{hy}$ is the total ICD purchases by hospital h in year y.

A.3 Other potential sources of price variation

In this section, I rule out potential sources of observed price variation between hospitals other than third degree price discrimination.

Quantity discounts:

I run three tests to rule out quantity discounts as the driver of price variation in the ICD industry:

1. I run two sets of regressions. First, I regress the log of prices at the product level on product-hospital and time fixed effects. Second, I regress the log of quantities purchased at the product level on product-hospital and time fixed effects. The purpose of these regressions is to find the residual variation in prices and quantities within a product-hospital over time. I report the R^2 values of these regressions in table 8. Regardless of how I define time, the R^2 of the price regressions is much higher than

the R^2 of the quantity regressions. This suggests that while the prices for a product within a hospital stays stable over time, quantities vary a lot. This first piece of evidence suggests that quantity discounts are unlikely to explain the large variation in prices that I observe in this industry.

Table 8: Variation in prices and quantities within a hospital over time

	R^2
Month level:	
log (prices)	0.93
log (quantities)	0.42
Quarter level:	
log (prices)	0.92
log (quantities)	0.54
Year level:	
log (prices)	0.93
log (quantities)	0.65

This table reports the R^2 values of regressions of the log of prices and quantities at the product level on product-hospital and time fixed effects.

2. Next, I conduct more explicit tests for the existence of quantity discounts. I regress log prices paid for each product on log quantities purchased, including time and product-hospital fixed effects. The exact specification is:

$$log(p_{jht}) = log(q_{jht}) + \theta_{jt} + \theta_t + \epsilon_{jht}$$

If quantity discounts exist, the same hospital should pay lower prices for the same product when they buy it in a larger quantity. Quantity discounts may exist at the product, brand, or manufacturer level, so I try three specifications in which I aggregate the quantity variable to the product, brand, and manufacturer level. I also aggregate time at the month, quarter and year level, to account for the possibility that quantity discounts may exist at a more aggregate level. The results of these regressions are in table 9 In all of these regressions, I find that a 1% increase in quantities purchased reduces prices by less than 0.01%. Thus, while quantity discounts do seem to exist in this industry, they do not seem to be substantial enough to explain the large variation in prices that I see in my data.

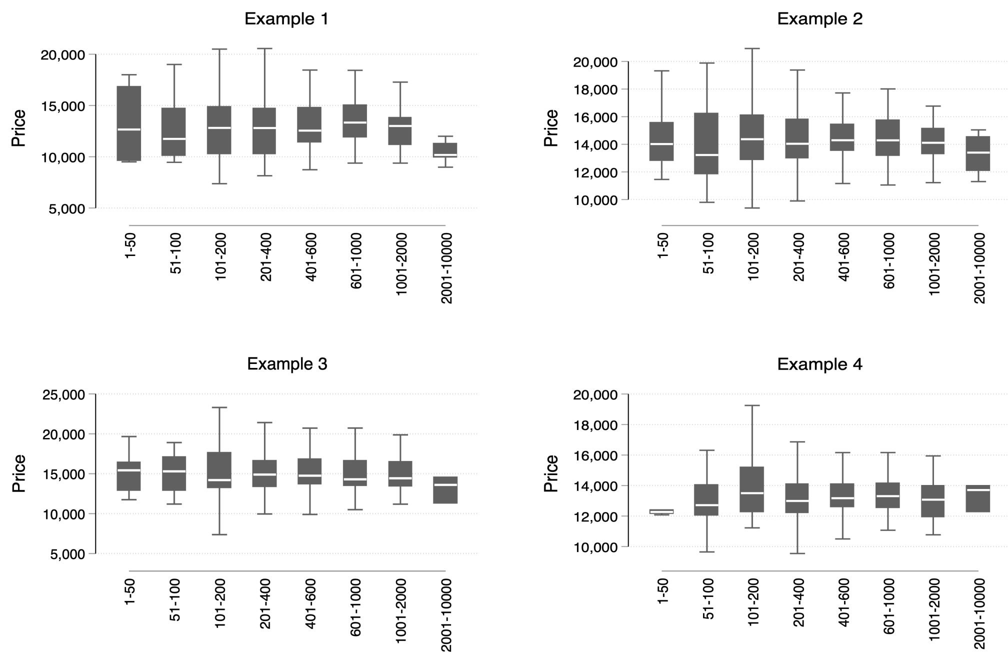
Table 9: Quantity discounts

	Month level:		
	SKU level log(price)	Brand level log(price)	manufacturer level log(price)
log(volume)	–0.010*** (0.001)	–0.007*** (0.001)	–0.008*** (0.001)
R^2	0.924	0.924	0.924
N	69,361	69,361	69,361
	Quarter level:		
log(volume)	–0.007*** (0.001)	–0.007*** (0.001)	–0.008*** (0.001)
R^2	0.916	0.916	0.916
N	46,849	46,849	46,849
	Year level:		
log(volume)	–0.003** (0.001)	–0.005** (0.002)	–0.005** (0.002)
R^2	0.927	0.927	0.927
N	20,966	20,966	20,966
Product-hospital FE	Y	Y	Y
Time FE	Y	Y	Y

This table reports results from a regression of log prices on log quantities, with product-hospital and time FE. I aggregate volumes at the SKU, brand and manufacturer level, and use month, quarter, and year to define time.

3. Third, if quantity discounts were significant, I would expect larger hospitals to pay lower prices. I have data on hospital bed-sizes, and figure 4 shows that the distribu-

Figure 4: Hospital size and prices



This figure has box plots of the top 4 SKUs (products) in terms of sales, over different hospital bed-sizes, where each box documents the variation in prices paid for the same product between hospitals of the same size. The upper hinge of each box has the 75th percentile of prices, the lower hinge has the 25th percentile

tion of prices looks quite similar across hospital sizes. I do not have data on hospital chain affiliation, so I can't rule out the possibility that hospitals with smaller bed-size might be getting better prices due to their affiliation to larger hospitals, i.e. that quantity discounts from the purchases of larger hospitals carry over to smaller ones.

Exclusive contracts:

Another possible driver of the variation in prices paid for the same hospitals could be exclusive contracts. I have two reasons to believe that these are not explaining the large variation in prices that I observe.

1. I find the fraction of total purchases by a hospital in each month from each manufacturer. I then perform two regressions. First, for each manufacturer, I regress the mean prices paid in a month by a hospital for an ICD from that manufacturer on

a dummy variable = 1 if the above fraction is 1 and 0 otherwise. This will give me information about whether exclusive contracts in this industry lead to lower prices. Second, for each manufacturer, I regress the mean prices paid in a month by a hospital for an ICD from that manufacturer on a dummy variable = 1 if the above fraction is greater than 0.8. This is my test for the presence of near-exclusive contracts. I add hospital $\times$ manufacturer and time FE to both these regressions, as I am interested in finding out whether prices within the same hospital vary depending on whether or not that hospital was buying exclusively from one manufacturer. I do these regressions for the two largest manufacturers in my data.

The results for these regressions are in table 10.

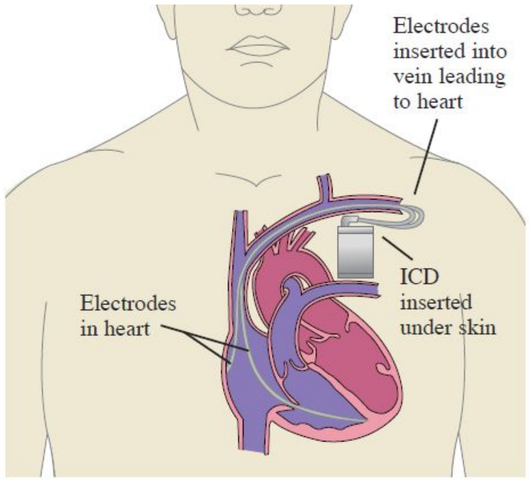
2. My conversations with electrophysiologists, analysts at GlobalData, and the supply chain director of a major hospital in Boston lead me to believe that exclusive contracts may not be the driving force behind price discrimination in the industry for ICDs. There are three reasons for this. First, physicians have a lot of influence over the devices that are purchased by the hospital. Second, hospitals prefer to contract with multiple manufacturers due to the risk of recalls, which are extremely common in this industry. Third, the industry is very concentrated, and sales representatives from each manufacturer are likely to be present in every hospital.

Table 10: Exclusive contracts

	Medtronic		St Jude Medical	
	log(mean price)	log(mean price)	log(mean price)	log(mean price)
exclusive	–0.007*		–0.019***	
	(0.003)		(0.003)	
almost exclusive		–0.002		–0.022***
		(0.003)		(0.003)
Constant	9.723***	9.722***	9.431***	9.432***
	(0.002)	(0.002)	(0.001)	(0.001)
R^2	0.436	0.436	0.753	0.753
N	21,738	21,738	14,274	14,274
Firm-hospital FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y

This table reports results from a regression of average log prices on dummy variables for exclusive and almost exclusive contracts, with manufacturer-hospital and time FE.

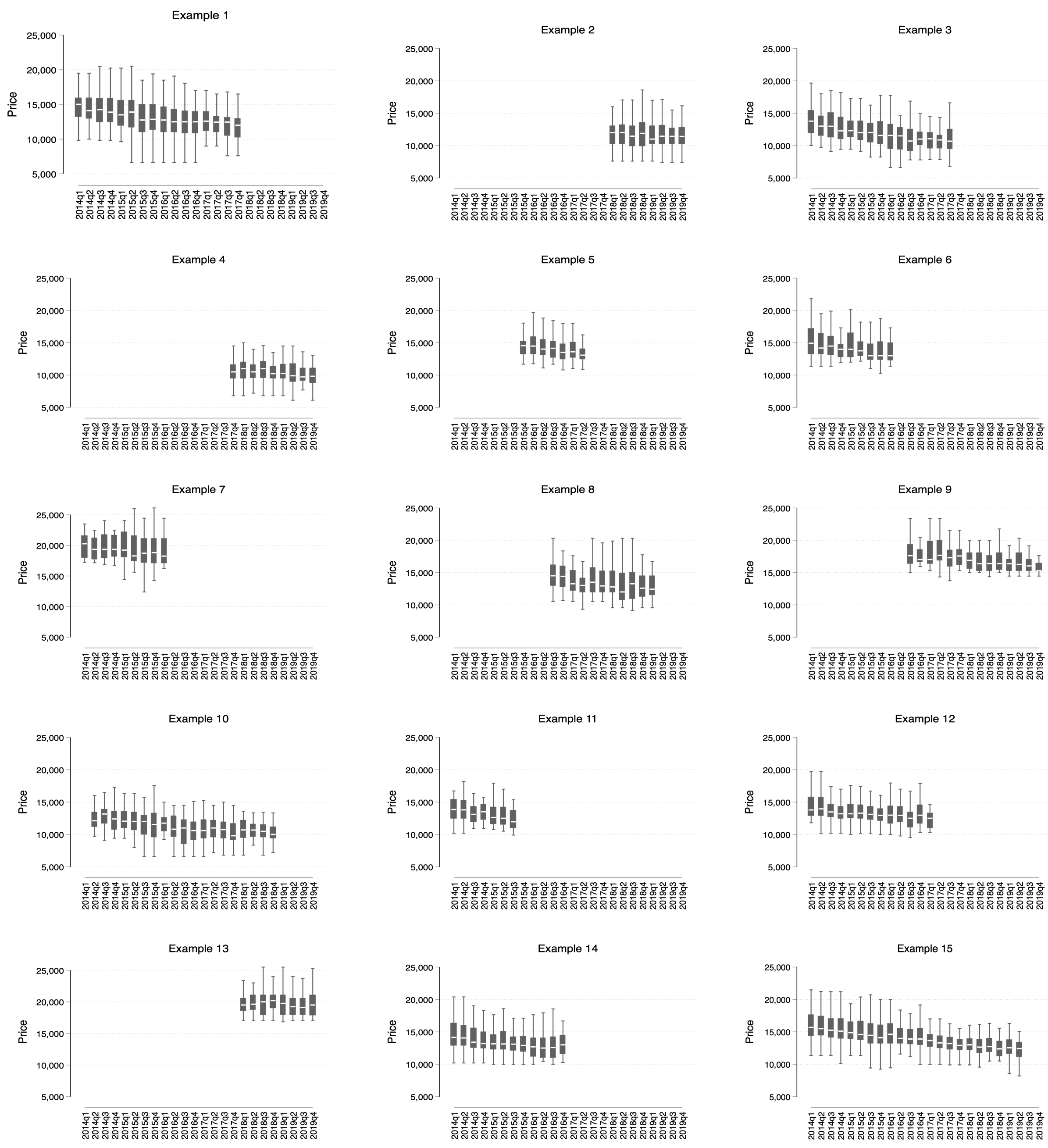
Figure 5



Source: https://www.chss.org.uk/heart-information-and-support/about-your-heart-condition/common-heart-conditions/heart-arrhythmias-2/icds-implantable-cardioverter-defibrillators/

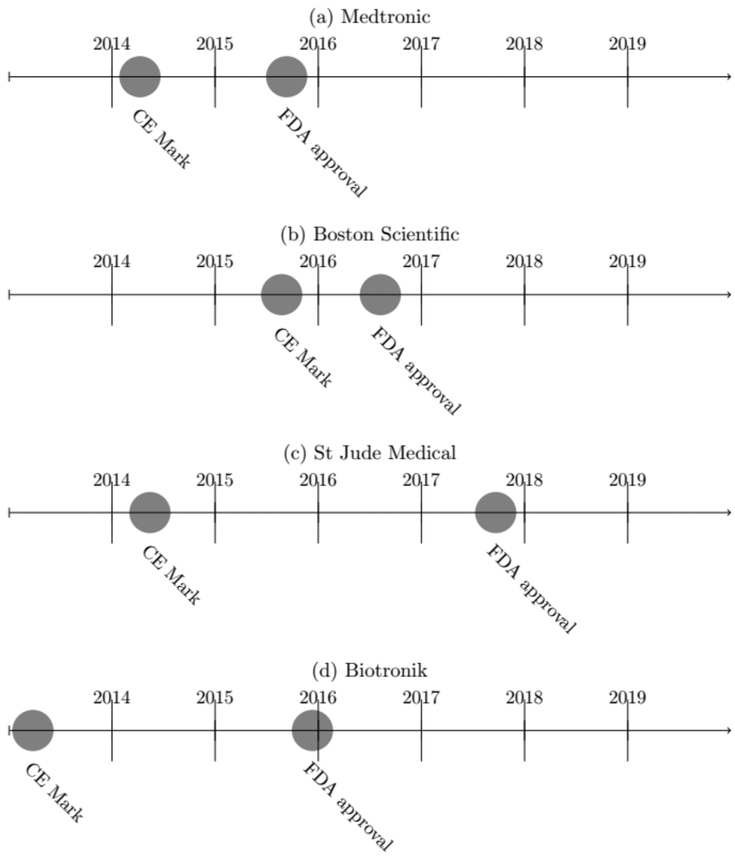
A.4 Additional figures and tables

Figure 6: Motivating fact 1: Price variation



This figure has box plots of prices of the top 15 products (in terms of sales), over time, where each box documents the variation in prices of the same product in a particular quarter between hospitals. The upper hinge of each box is the 75th percentile of prices, the lower hinge is the 25th percentile. For this figure, I drop product-quarters with sales less than 50 units.

Figure 7



This figure displays timelines of the approval of the first MRI-safe ICDs in the European Economic Area (CE Mark) and the US (FDA).

Table 11: Logit results

	(1) First stage	(2) Logit
demand_instruments0	0.0143*	
	(0.00762)	
demand_instruments1	-0.0187***	
	(0.00138)	
demand_instruments2	0.0175**	
	(0.00744)	
demand_instruments3	-0.000269	
	(0.000579)	
demand_instruments4	-0.00647***	
	(0.000568)	
df4=1	0.0505***	0.251***
	(0.00398)	(0.0130)
single chamber	-0.141***	-0.689***
	(0.00381)	(0.0447)
mri-safe	0.274***	0.615***
	(0.0108)	(0.0433)
prices		-3.390***
		(0.312)
Constant	1.345***	
	(0.00444)	
Observations	25015	25015
F		89.54

Standard errors in parentheses
product and hospital FE and year FE included.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Diversion

			Medtronic		St Jude Medical	
	MRI-safe	Outside	MRI-unsafe	MRI-safe	MRI-unsafe	MRI-safe
Medtronic	MRI-unsafe	0.35	0.13	0.13	0.08	0.08
	MRI-safe	0.33	0.10	0.19	0.07	0.12
St Jude Medical	MRI-unsafe	0.34	0.11	0.11	0.11	0.12
	MRI-safe	0.35	0.05	0.16	0.08	0.16

This table is the mean diversion matrix for products of the most popular brand from the top 2 firms in my data, averaged over hospitals, products and time.
The MRI-safe products are in the gray regions of the table

Table 13: Diversion

			Medtronic										St Jude Medical					
	Product	MRI-safe	A	B	C	D	E	F	G	H	I	J	A	B	C	D	E	F
Medtronic	A	No	0.34	0.08	0.11	0.10	0.17	0.12					0.11	0.05	0.07	0.09		
	B	No	0.09	0.34	0.14	0.19	0.09	0.13	0.10	0.16	0.12		0.09	0.07	0.08	0.09		
	C	No	0.11	0.11	0.34	0.16	0.09	0.17	0.11		0.13		0.10	0.06	0.07	0.09		
	D	No	0.10	0.13	0.15	0.36	0.12	0.16	0.11	0.19	0.18	0.13	0.11	0.08	0.09	0.09	0.09	0.06
	E	No	0.16	0.09	0.10	0.14	0.36	0.11	0.09	0.12	0.13	0.12	0.11	0.06	0.10	0.10		
	F	No	0.10	0.10	0.16	0.18	0.10	0.34	0.08	0.18	0.14		0.11	0.06	0.08	0.08		
	G	Yes		0.08	0.07	0.14	0.13	0.06	0.33	0.17	0.23	0.12	0.07	0.05	0.06	0.07		
	H	Yes		0.07		0.15	0.12	0.10	0.10	0.33	0.19	0.26	0.12	0.07	0.09	0.07		
	I	Yes		0.07	0.08	0.14	0.11	0.10	0.17	0.24	0.35	0.20	0.09	0.05	0.07	0.07	0.13	0.10
	J	Yes				0.10	0.11		0.09	0.26	0.26	0.33	0.08	0.05	0.07	0.06	0.12	0.10
St Jude Medical	A	No	0.11	0.08	0.11	0.13	0.12	0.12	0.07	0.16	0.13	0.09	0.34	0.08	0.11	0.12		
	B	No	0.09	0.10	0.10	0.12	0.10	0.10	0.06	0.12	0.13	0.11	0.12	0.34	0.10	0.12	0.13	0.11
	C	No	0.10	0.09	0.11	0.14	0.13	0.11	0.07	0.15	0.13	0.11	0.14	0.09	0.34	0.11	0.15	0.11
	D	No	0.10	0.09	0.12	0.12	0.11	0.10	0.07	0.12	0.11	0.08	0.13	0.08	0.10	0.35		
	E	Yes				0.06					0.20	0.14		0.08	0.08		0.34	0.15
	F	Yes				0.04					0.17	0.12		0.07	0.07		0.17	0.35

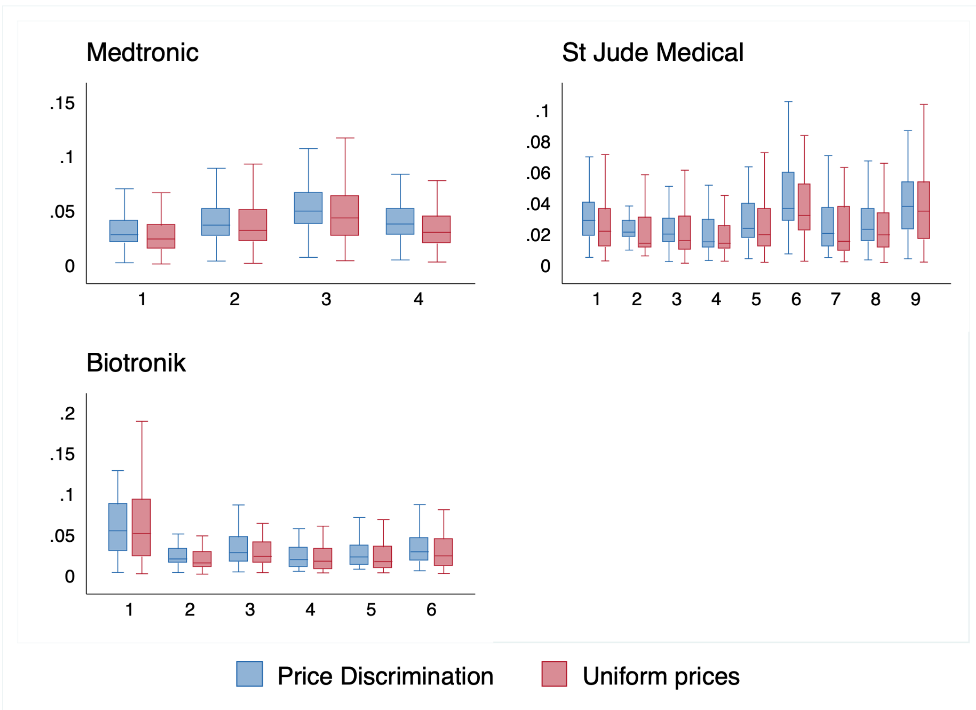
This table is the mean diversion matrix for products of the most popular brand from the top 2 firms in my data, averaged over hospitals and time.
The MRI-safe products are in the gray regions of the table
I do not include products that only appeared for one period
The diagonal elements have diversion to the outside good.

Table 14: Elasticities

			Medtronic										St Jude Medical					
	Product	MRI-safe	A	B	C	D	E	F	G	H	I	J	A	B	C	D	E	F
Medtronic	A	No	-5.12	0.38	0.58	0.58	0.81	0.65					0.52	0.23	0.35	0.39		
	B	No	0.51	-5.13	0.75	1.08	0.52	0.79	0.58	1.29	0.81		0.48	0.31	0.39	0.44		
	C	No	0.58	0.52	-5.03	0.89	0.52	0.96	0.62		0.81		0.49	0.28	0.35	0.43		
	D	No	0.52	0.57	0.68	-4.87	0.55	0.84	0.51	1.34	0.97	0.73	0.52	0.30	0.41	0.38	0.40	0.26
	E	No	0.80	0.42	0.49	0.81	-4.91	0.62	0.42	0.86	0.71	0.65	0.50	0.26	0.46	0.39		
	F	No	0.54	0.46	0.70	0.92	0.53	-5.13	0.43	1.37	0.83		0.51	0.24	0.36	0.34		
	G	Yes		0.35	0.33	0.68	0.60	0.32	-5.10	1.35	1.33	0.69	0.34	0.19	0.27	0.30		
	H	Yes		0.21		0.56	0.45	0.48	0.37	-5.17	0.83	1.13	0.35	0.21	0.31	0.21		
	I	Yes		0.28	0.33	0.58	0.44	0.43	0.78	1.72	-4.62	0.91	0.38	0.19	0.27	0.26	0.50	0.36
	J	Yes				0.42	0.44		0.45	1.70	1.27	-4.85	0.34	0.18	0.26	0.24	0.48	0.36
St Jude Medical	A	No	0.58	0.40	0.54	0.70	0.63	0.66	0.39	1.26	0.78	0.58	-4.86	0.32	0.48	0.51		
	B	No	0.60	0.55	0.60	0.72	0.64	0.67	0.41	1.02	0.83	0.68	0.63	-4.73	0.51	0.57	0.60	0.47
	C	No	0.57	0.47	0.57	0.79	0.72	0.63	0.42	1.16	0.78	0.65	0.67	0.37	-4.93	0.51	0.62	0.43
	D	No	0.62	0.49	0.65	0.71	0.64	0.62	0.42	1.02	0.71	0.51	0.67	0.37	0.47	-4.77		
	E	Yes				0.32					1.13	0.80		0.29	0.28		-4.49	0.52
	F	Yes				0.25					1.03	0.75		0.29	0.29		0.78	-4.34

This table is the mean elasticities matrix for products of the most popular brand from the top 2 firms in my data, averaged over hospitals and time.
I do not include products that only appeared for one period
The diagonal elements have own price elasticities, and off diagonal elements cross-price elasticities.
The missing values are when the two brands did not exist at the same time
The MRI-safe products are in the gray regions of the table
For example, this table tells us that a 1% increase in price of Product A by St Jude Medical increases demand for Product B by St Jude Medical by 0.63%

Figure 8



This figure shows the expected shares of the products that were offered in 2019 under price discrimination and uniform pricing. The x-axis has products, and the y axis has shares. For each case, the upper hinge of the box is the 75th percentile of shares, and the lower hinge is the 25th percentile of shares, averaged for the 2 periods in 2019. I report the average over the two periods in 2019.