ESSAYS IN INDUSTRIAL ORGANIZATION AND HEALTH ECONOMICS

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Abstract

This dissertation addresses questions in the pharmaceutical and medical device industries. In the first chapter, I study the welfare effects of price discrimination in the medical device industry. In the second chapter, I document shifts in the marketing and prescription behavior for a drug after it is acquired. In the third chapter I study the reputation spillover effects of a major medical device recall.

Chapter 1: 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 were forced to 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 can cause an increase in product variety, which can lead to different welfare predictions. If we fail to

account for a manufacturer's ability change their product offerings in response to a uniform pricing policy, we can overestimate the effects of uniform pricing on hospital welfare, underestimate the effect of uniform pricing on the take up of older, lower quality products, and we may overestimate or underestimate the effects of uniform pricing on manufacturer profitability.

Chapter 2: In this chapter, Motaz Al-Chanati and I document novel evidence of a shift in marketing and prescription behavior for a drug after its acquisition. Network size is highly relevant for this industry, as advertising to physicians (known as detailing) typically involves in-person meetings between sales representatives and physicians. We use 10 drug acquisitions in 2015-2016 to document patterns in the data consistent with firms leveraging their existing physician-sales representative networks to market a drug after they acquire it. We also show that this shift in marketing strategy translates into prescription behavior, i.e. after a drug is acquired, physicians that have prior relationships with the acquiring firm increase their prescriptions of it.

Chapter 3: I analyze the effects a major product recall in the implantable medical device industry on the sales of other products manufactured by the recalling firxm. I find that after the recall, consumers substituted away from the recalling firm's other products that were not recalled, and toward the products of the recalling firm's rivals. I also quantify the heterogeneity in the response to this recall based on two consumer characteristics: firm loyalty and exposure. I construct proxies for these characteristics, and I find that while consumers that were more exposed to the recall did not have a significantly different response to it, consumers that were more loyal to the recalling firm had smaller responses to it.

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1 Chapter 1: Price Discrimination and Product Variety: The Case Of Implantable Medical Devices [1]

1.1 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 (see Appendix 1.9.1). 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

[1] I thank Washington Center for Equitable Growth for funding this 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."*

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 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 period, I assume that manufacturers observe the fixed cost of offering each product in that period, 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 period.

[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.

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 equilibrium 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 (consumer) surplus by 7.1%.[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 9.2% and 1.5% respectively, while the profits for the third manufacturer in my data would increase by 2.6%. Expected total surplus would drop by 7.1%.

Under a counterfactual that allows manufacturers to continue offering their older MRI-safe products for a longer period, I find different results under a uniform pricing policy. If fixed costs are too high, then no manufacturer continues to offer an additional MRI-unsafe product, but there are many equilibria in which at least one and a maximum of two additional MRI-unsafe products get offered. When additional

[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

products are offered, product variety increases, and when two rivals continue to offer an additional product, prices fall due to stronger manufacturer competition between the additional rival products. This causes expected hospital surplus to increase, and the welfare losses due to uniform prices now drop by only up to 3.6% relative to the price discrimination case. 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 up to 10.3%. On the manufacturers' side, profitability may increase or decrease relative to the uniform pricing case with fixed product offerings, depending upon whether a rival chooses to offer an additional product and the value of fixed costs at which a manufacturer chooses to offer an additional product. I find that the largest manufacturer in my data is always weakly worse off relative to the uniform pricing with fixed product offerings case, while the other two manufacturers may be better or worse off. In these equilibria, the drop in expected total surplus relative to the price discrimination case ranges from 4.6-8.4%. Thus, failing to account for manufacturers' ability to change their product offerings in response to a uniform pricing policy the overestimates the effects of uniform pricing on hospital welfare, underestimates the effect of uniform pricing on the take up of older, lower quality products, and may overestimate or underestimate the effects of uniform pricing on manufacturer profitability.

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.[5] I endogenize product offerings of manufacturers 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 offsets these welfare losses, and in some cases may increase 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

be interpreted as hospital surplus, keeping insurance premiums fixed.

[5]Grennan (2013) models the price-setting process as a Nash-in-Nash bargaining model. See

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) studies the case of the copyright law in the video rental industry, and 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 (2020). 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 following 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 1.2 describes the industry for ICDs, the new MRI-safe technology that was introduced in the US, and my data sources. Section 1.3 presents three motivating facts which should convince the reader that ICDs are an appropriate context for my research question. Section 1.4 describes the empirical model of supply and demand, and section 1.5 describes how I estimate the model. My estimation results are in section 3.4. The counterfactual description and results are in section 1.7. I conclude in section 3.6.

1.2 Institutional setting and Data

1.2.1 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.[6] An ICD is implanted in a patient's chest, and connected to their heart via leads (see figure 1.7 in appendix 1.9.4). It reduces the risk of death due to sudden

footnote 17 for details about why I assume a Nash Bertrand equilibrium.

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

cardiac arrest by shocking an implanted patient's heart when it detects a dangerously abnormal heart rate.

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)).[7] The causes and effects of the lack of price transparency in this industry have often been a subject of discussion in the medical literature.[8]

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).

1.2.2 MRI-safe ICDs

Magnetic Resonance Imaging (MRI) scans are contraindicated in patients with traditional ICDs. This is because the magnetic fields formed by MRI machines can

[7] 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.

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

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, 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.[9]

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 1.9 in Appendix 1.9.4). 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.

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

1.2.3 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.[10] The healthcare facilities in this database are anonymous, and the only information I have about them are 1) their census region (Midwest, Northeast, 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.[11] 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

[10]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 1.9.2. 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.

[11]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 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 10.

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 1.9.2 for details).

My data cleaning process has been described in Appendix 1.9.2. 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.

1.3 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 is prevalent 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.

1.3.1 Price discrimination

In the Implantable Medical Device industry, different hospitals pay different prices for the same product (SKU). Examples of this can be seen in figure 1.1, 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 1.8 in Appendix 1.9.4 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 1.9.3.

1.3.2 MRI-safe ICDs

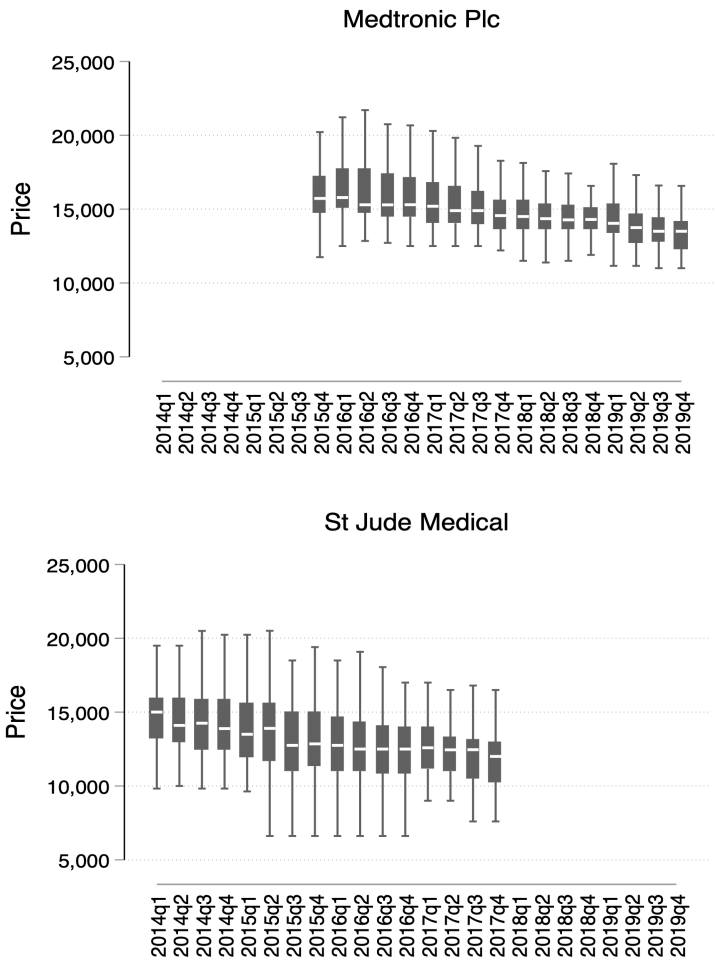
The first MRI-safe ICD received FDA approval in late-2015, after which manufacturers started phasing out their older, MRI-unsafe ICDs. The top panel of figure 1.2 shows that by 2019, only 2 out of 19 products offered by the three manufacturers in my dataset were MRI-unsafe. The bottom panel of figure 1.2 shows that MRI-safe ICDs account for almost all ICD sales in my sample by 2019.

Table 1.1 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 1.1, 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 1.1 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.

Figure 1.1: 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 1.1: 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.

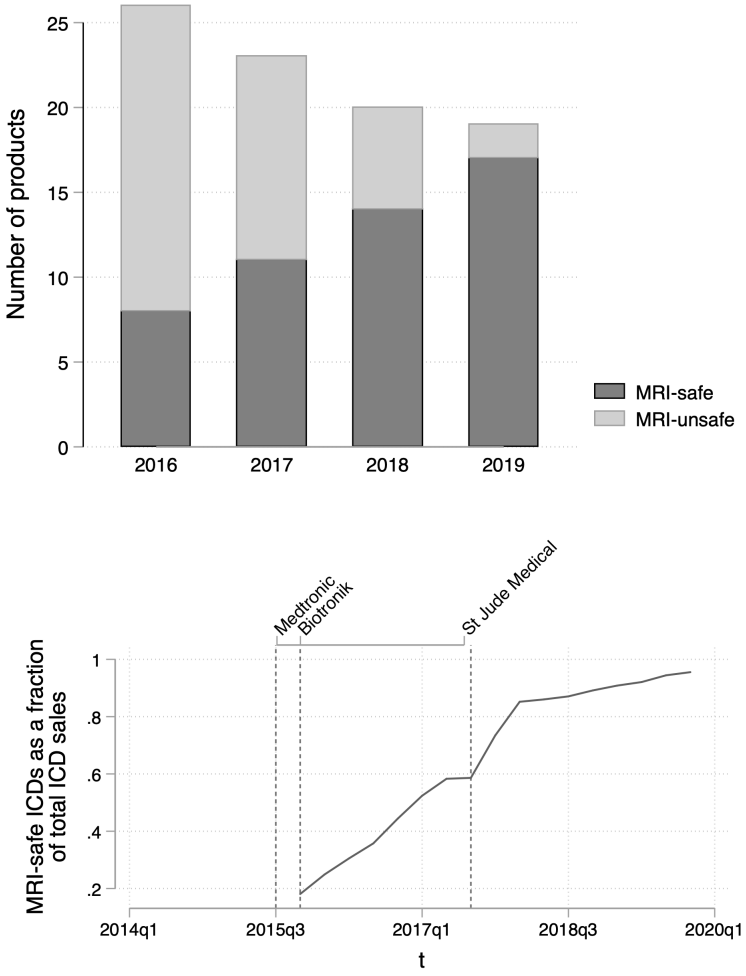
1.4 Empirical Model

1.4.1 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 period, manufacturers observe the fixed costs of offering each product and simultaneously choose their product offerings.
- **Stage 2:** After choosing their product offerings, in each period manufacturers observe demand and marginal cost shocks, and simultaneously set prices in a Nash Bertrand game.

Figure 1.2: 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 10.

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.

1.4.2 Demand

A market is a hospital in a six month period, and a product is an SKU.[12] 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 1.9 in appendix 1.9.3).[13]

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[14]

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

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 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

[12] 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.

[13] 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.

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

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. $\beta^i_{\mathbf{x}}$ 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. $\beta^i_c = \sigma_c \nu^i_c$, where $v^i_c \sim N(0,1)$. [15]
2. $\beta^i_p = e^{\beta_p + \sigma_p \nu^i_p}$, where $\nu^i_p \sim N(0,1)$
3. $\beta^{\mathbf{i}}_{\mathbf{x}} = \beta_{\mathbf{x}} + \sigma_{\mathbf{x}} \nu^{\mathbf{i}}_{\mathbf{x}}$, $\sigma_{dualchamber} = 0$, $\sigma_{DF4} = 0$, $\nu^i_{MRI} \sim N(0,1)$
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^i_c, ν^i_p, and ν^i_{MRI} 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

[15] β^i_c is mean zero because the constant could not be distinguished from brand-hospital fixed effects.

coefficient on prices follows a log-normal distribution to ensure that β_p^i is always positive. I set $\sigma_{dualchamber}$ 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.[16]

1.4.3 Supply

Stage 2: In stage 2, manufacturers observe the realizations of the demand and marginal cost shocks (i.e. ξ_{jht} and ω_{jht}), and simultaneously set prices in a Nash

[16]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). If I expand the choice sets of my agents by values for zero shares, 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.

Bertrand equilibrium. The assumption 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. [17] The profit function of a manufacturer f in period t is as follows:

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

J_{ft} is the set of product offerings of the manufacturer in period t (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-period 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 1.9.2. F_{jt} is the fixed cost of offering a product in each period. It is incurred if j is offered in period t.

I assume that the log of the marginal cost of selling a product depends upon its characteristics, year fixed effects, and a random shock. It has the following functional form:

[17] 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 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 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.

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

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

Stage 1: At the beginning of each period, 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 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 Subgame Perfect 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 $j \in J_{ft}$, where J_{ft} is the set of observed product offerings by manufacturer f in period t. It must be that:

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

where J_{-ft} denotes the observed product offerings of other manufacturers, $VP_{ft}(J_{ft}, J_{-ft})$ denotes variable profits of a manufacturer f in period t at the observed product offerings, and $VP(J_{ft}\backslash j, J_{-ft})$ denotes variable profits of a manufacturer if they drop

[18] $VP_{ft}(J_{ft}, J_{-ft}) = VP_{ft}(J_{ft}, J_{-ft}; \beta, \sigma, \gamma, \omega, \xi)$

j, keeping all other offerings (by f and competitors) fixed. [18]

In words, if a product j is offered by manufacturer f in period t, 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 period t, or if $j \notin J_{ft}$ it must be that

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

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

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.

1.5 Estimation

1.5.1 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, $\gamma_{\mathbf{w}}$ 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

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

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 $\Delta_{ht}^{jj} = \frac{\partial s_{jht}}{\partial p_{jht}}$, and $\Delta_{ht}^{jk} = \frac{\partial s_{kht}}{\partial p_{jht}}$ 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. Formally,

$$\omega_{\mathbf{ht}} + \mathbf{W_t} \gamma_{\mathbf{w}} = \log(\Delta_{ht}^{-1} \mathbf{s_{ht}}(\mathbf{p}) + \mathbf{p_{ht}})$$

$$\implies \omega_{\mathbf{ht}} = \log(\Delta_{ht}^{-1} \mathbf{s_{ht}}(\mathbf{p}) + \mathbf{p_{ht}}) - \mathbf{W_t} \gamma_{\mathbf{w}} \tag{6}$$

Once I enter my demand estimates into equation 6, the above equation is linear in $\gamma_{\mathbf{w}}$.

I make the following assumption:

$$E(\xi_{ht} | \mathbf{Z}_{ht}) = E(\omega_{ht} | \mathbf{Z}_{ht}) = 0$$

where $\mathbf{Z}_{ht}$ is the set of exogenous regressors and instruments. 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 instruments would capture the changing marginal costs of providing a certain characteristic to a hospital over time.

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.

1.5.2 Fixed costs

In this stage of the analysis, fixed cost bounds for each brand are estimated. The upper bound of fixed costs, $\bar{F}_{jt}$ can be estimated for each product j observed in the data in period t. 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 $VP_{ft}(J_{ft}, J_{-ft}|\xi^d, \omega^d, \beta, \gamma, \sigma)$.

J_{ft} is the set of product offerings at the observed equilibrium.

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

4. $\bar{F}_{jt} = 1/n \sum_{d=1}^{n} [VP_{ft}(J_{ft}, J_{-ft}|\xi^d, \omega^d, \beta, \gamma, \sigma) - VP_{ft}(J_{ft}\backslash j, J_{-ft}|\xi^d, \omega^d, \beta, \gamma, \sigma)]$

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

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

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

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

4. $\underline{F}_{j\prime t} = 1/n \sum_{d=1}^{n} [VP_{ft}(J_{ft} \cup j\prime, J_{-ft})|\xi^d, \omega^d, \beta, \gamma, \sigma) - VP_{ft}(J_{ft}, J_{-ft}|\xi^d, \omega^d, \beta, \gamma, \sigma)]$

My setting poses a complication: all products do not enter the choice sets of all hospitals in each period. Therefore, while estimating lower bound of the fixed cost of a product, I have to make an assumption about which hospitals' choice sets a product $j\prime$ would enter if it were offered in period t. 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 period t.[19]

Selection: In a period that product j is offered, equation 3 gives an upper bound on fixed costs, and in a period it is not offered, equation 4 gives a lower bound.

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

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 period. This is the selection issue described in Pakes et al. (2015). To circumvent this issue, I make the following assumptions on the support of fixed costs, which are very similar to those that Eizenberg (2014) makes:

1. F_{jt} is bounded from above.

2. F_{jt} belongs to the support of the expected changes in variable profit from adding or removing a single product of firm f, across all the products of firm f.

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.

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 using the assumptions outlined above, whenever an upper (lower) bound is missing, I replace it with the highest (lowest) estimated hospital level average upper (lower) bound for that firm.

Formally, for product j belonging to manufacturer f that is offered in period t, I use UB_{jt} and LB_{jt} defined as follows:

$$UB_{jt} = \frac{\bar{F}_{jt}}{H_{jt}}$$

$$LB_{jt} = min_{\{k \in J^f, p \in T\}} \left(\frac{\underline{F}_{kp}}{H_{kp}} \right)$$

For a product $j\prime$ belonging to firm f that is not offered in period t,

$$UB_{j\prime t} = max_{\{k \in J^f, p \in T\}} \frac{\bar{F}_{kp}}{H_{kp}}$$

$$LB_{j\prime t} = \frac{\underline{F}_{j\prime t}}{H_{j\prime t}}$$

where J^f is the set of products belonging to manufacturer f and T denotes the set of 6 years from 2014-2019 in my sample.

1.6 Results

Table 1.2 displays the demand estimates and second stage cost estimates.[20] 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 suggest that 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. Table 1.3 reports average elasticities

[20] See table 1.12 in appendix 1.9.4 for logit results

over products, hospitals and time, for the most popular brands of the manufacturers in my data, by MRI-safety type.[21] Columns (2)-(7) report the percent change demand for the row product for a 1% increase in prices of the column product. The cross price elasticities suggest that: 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.

Average marginal cost (γ_w) estimates are reported in the third column of table 1.2. Implied average marginal costs are in table 1.4. 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.[22] 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.

Figure 1.3 shows the distributions of the estimated per-hospital upper and lower bounds of fixed costs of offering each product in a six-month period (before accounting for selection). Fixed costs are a substantial fraction of average revenues from each

[21] See table 1.13, 1.16 and 1.14 in appendix 1.9.4 for the diversion table, and the full elasticities and diversion matrices.

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

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. Table 1.15 in Appendix 1.9.4 shows the estimated upper and lower bounds of fixed costs for each product (after I account for selection) in the first period of 2019.

Table 1.2: 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.

1.7 Counterfactual

1.7.1 Description

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 prod-

Table 1.3: Price elasticities

			Medtronic		St Jude Medical		Biotronik	
	MRI-safe	(1) Own	(2) MRI-unsafe	(3) MRI-safe	(4) MRI-unsafe	(5) MRI-safe	(6) MRI-unsafe	(7) MRI-safe
Medtronic	MRI-unsafe	-5.03	0.65	0.81	0.39	0.33	0.39	0.26
	MRI-safe	-4.94	0.43	1.04	0.27	0.43	0.42	0.46
St Jude Medical	MRI-unsafe	-4.82	0.62	0.73	0.51	0.53	0.36	0.29
	MRI-safe	-4.41	0.29	0.92	0.29	0.65		0.27
Biotronik	MRI-unsafe	-5.19	0.48	0.68	0.47			
	MRI-safe	-5.27	0.32	0.99	0.26	0.38		0.39

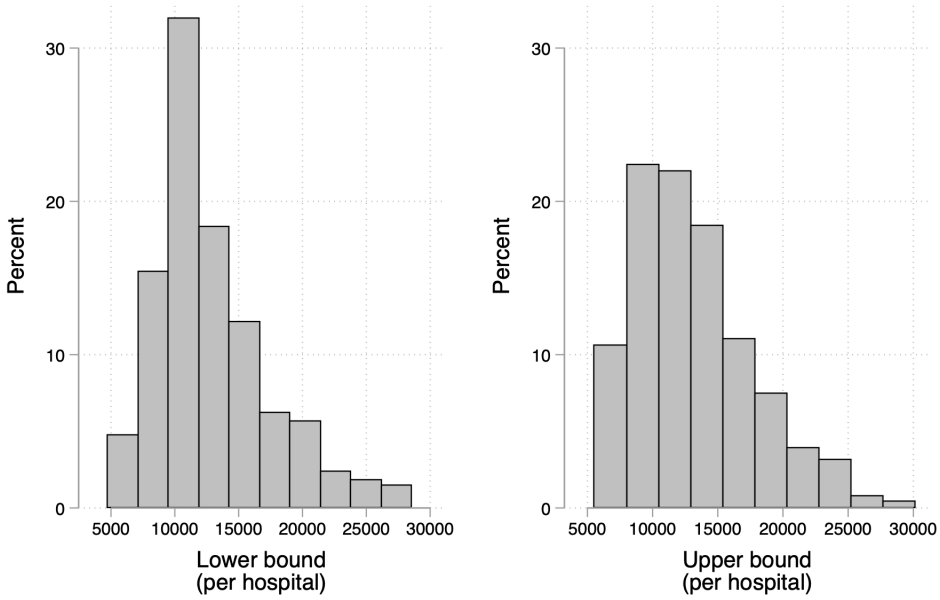
This table is the mean elasticities matrix for products of the most popular brand from the firms in my data, averaged over hospitals, products and time. The MRI-safe products are in the gray regions of the table. Column (1) reports average own price elasticities, while columns (2)-(4) report average 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 1.4: 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.

Figure 1.3: Fixed cost distributions



This figure shows the distribution of the estimated lower and upper per-hospital fixed cost bounds. Lower bounds are estimated for products that were not offered in a period, and upper bounds are estimated for products that were offered in a period.

ucts, and use them to indirectly price discriminate? How would this affect consumer welfare and the take-up of newer and better technologies?

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 possible equilibria under this uniform pricing assumption.

Each SPNE for period t 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 $J_t \times 1$ vector, where J_t is the number of all products that were offered in at least one period during from 2014 until period t. If product j is offered in period t, then the jth element of this vector will take a value 1, and 0 otherwise. If J_t products existed from 2014-2019, 2^{J_t} such vectors are possible.

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.,

$$\pi_{ft} = \underbrace{\sum_{h \in H_{jt}} \sum_{j \in J_{ft}} (p_{jt} - c_{jht}) s_{jht}(\mathbf{p}) M_{ht}}_{\text{Variable profits } VP_{ft}} - \sum_{j \in J_{ft}} F_{jt} \tag{7}$$

Equation (7) is different from equation (1) because prices in equation (7) are p_{jt}, assumed to be the same for a product j at time t across all hospitals.

From these 2^{J_t} vectors, I can find the vectors that cannot be ruled out as 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 deter-

mine which equilibrium would actually hold, because fixed costs are only partially identified.

I find the set of possible equilibria by checking whether each of the 2^{J_t} vectors of possible product offerings is an equilibrium for some fixed cost values within the estimated intervals. For each vector, 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.[23] I use this method to eliminate vectors that have a profitable deviation. Finally, I am left with the set of vectors that have no profitable deviation, which are my final set of possible equilibria.

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} vectors, which is computationally difficult. I take the following steps to reduce the computational burden of this problem:

- I restrict my counterfactual analysis to the first six-month period of 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

[23]Here is a simplified example: Suppose $J = 6$, and there is a single manufacturer f that owns all these products. 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 $\bar{F}_{jt}$, 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 $\underline{F}_{jt}$, it is a profitable deviation. If not, I check the third deviation and so on

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.
  - 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.
  - Finally, I eliminate each that would never continue to be offered, even if no other product was continued to be offered. To do this, I start at the set of observed product offerings in the first period of 2019. I take the set of products that exited prior to this period, and one by one I reintroduce each of these products, and check whether this reintroduction is a profitable deviation for some fixed cost in my estimated interval. I drop the products which would not continue to be offered for any value of fixed cost in the estimated intervals. The idea is that in the absence of entry by a rival, if there is no value of fixed cost for which it is profitable for a firm to continue offering a product under uniform pricing, then this product would never continue to be offered. Thus, I am left with 12 products.
  - Finally, of these 12 products, I keep the top 8 products in terms of the number of hospitals that they would be reintroduced in.

After making all the simplifying assumptions above, I am left with 8 products that the 3 manufacturers are allowed to vary in the first period of 2019 under a uniform pricing counterfactual. None of these 8 products were offered in 2019, and none of them were MRI-safe. 2 of these products belong to St Jude Medical, 1 belongs to Medtronic, and the remaining products belong to Biotronik.

1.7.2 Results

I generate three sets of results: First, I re-simulate 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.[24] 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, and the procedure described above.

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

[24]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.

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.

Results without product entry: Figure 1.4 shows that if we keep product offerings fixed, expected prices for each product under a uniform pricing counterfactual are higher than the median expected prices under price discrimination. There is some degree of heterogeneity in strategies between manufacturers; Biotronik and St Jude Medical target their highest willingness-to-pay consumers by always setting its uniform prices above the 75th percentile of expected prices under price discrimination. Medtronic on the other hand, prices its products closer to (or slightly higher than) the median under price discrimination. The shares version of this figure can be found in figure 1.10 in appendix 1.9.4.

Panel A of table 1.8 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). The profits of Medtronic and St Jude Medical to drop by 9.2% and 1.5% (row 1) respectively, while the profits of Biotronik increase by 2.6%. Due to the higher prices and aggregate substitution away from ICDs, there is a loss in expected aggregate hospital surplus of 7.5% (row 2). However, there is some variation in this result, as 25% of the hospitals in my sample gain and the remaining lose from uniform pricing. These gains come for hospitals that now pay a lower price for products due to uniform pricing. Row 5 compares total surplus under uniform pricing, calculated as the sum of variable profits and hospital surplus, to total surplus under price discrimination. Total surplus under uniform pricing drops by 7.1%: a result that is driven by the drop in variable profits for the two largest firms in my data, and

the drop in hospital surplus.

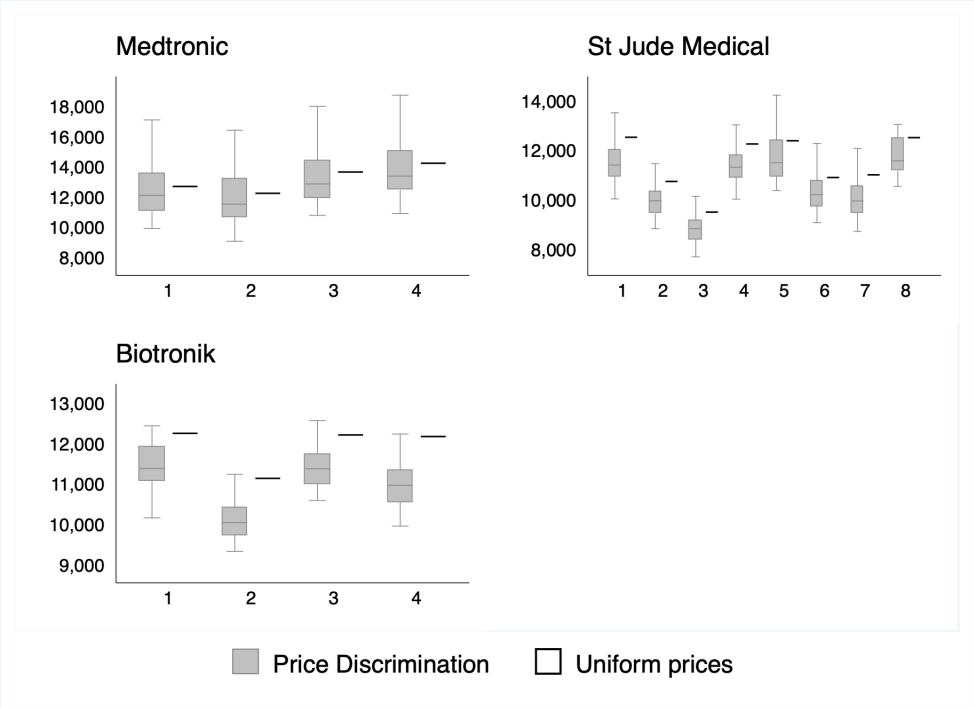
My results are consistent with Grennan (2013), who finds that when hospitals are price takers, there is a reduction in competition under uniform pricing, and manufacturers choose to price to their more captive markets, which increases prices, and lowers aggregate hospital surplus. Grennan (2013) finds that hospitals would need to have large increases in their bargaining abilities for them to have aggregate welfare gains from uniform prices. In the next section, I show that under uniform pricing, if fixed costs are low enough, manufacturers would engage in additional indirect 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 (when multiple manufacturers re-introduce their products), 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. However, the adoption of newer, higher quality products would reduce.

Table 1.5: Additional entry under uniform pricing

(Medtronic, St Jude Medical, Biotronik)	Number of equilibria
(0,0,0)	1
(1,0,0)	1
(0,1,0)	2
(0,0,1)	5
(0,0,2)	4
(0,1,1)	10

This table reports the number of equilibria of each type. For example, the last row of the table tells us that there are 10 equilibria in which one product of St Jude Medical and one product of Biotronik enters. The second last row tells us that there are 4 equilibria in which 2 products of Biotronic enter.

Figure 1.4: Counterfactual prices - holding product offerings fixed



This figure shows the expected prices of the products that were offered in the first period of 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.

Table 1.6: Prices when a rival enters

Firm	No entry	Rival entry
Biotronik	12,052	11,996
Medtronic Plc	13,266	13,180
St Jude Medical	11,591	11,540

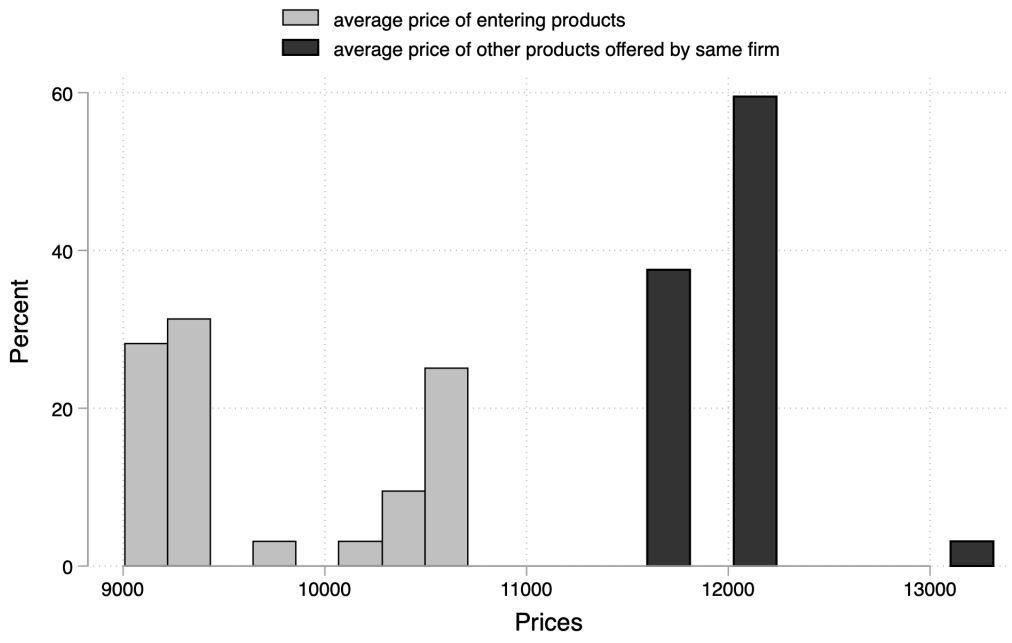
This table shows the average prices of a firm's products when there is additional entry by a rival (col 3) and when there is no entry (col 2)

Table 1.7: Prices when own product enters

Firm	No entry	Own entry
Biotronik	12,052	12,151
Medtronic Plc	13,266	13,317
St Jude Medical	11,591	11,654

This table shows the average prices of a firm's MRI-safe products when it is the only firm to introduce an additional MRI-unsafe product (col 3) and when there is no entry (col 2)

Figure 1.5: Prices of entering products



This figure shows us the distribution of the average price of the entering product (blue) and the price of other products offered by the same firm (green), for each product that enters in an equilibrium.

Table 1.8: Counterfactual analysis

A: No product entry [a]	Price Discrimination	Uniform prices
1.Expected variable profits (million $)		
Medtronic	34.7	31.5
Δ (%)		**-9.2**
St Jude Medical	13.0	12.8
Δ (%)		**-1.5**
Biotronik	3.9	4.0
Δ (%)		**2.6**
2. Expected hospital surplus (million $)	94.3	87.2
Δ (%)		**-7.5**
3. Δ Expected total surplus (%)		**-7.1**
4. MRI-safe ICD share	0.97	0.97
Δ (%)		**0**
5. Average inside good share	0.19	0.16
Δ (%)		**-15.7**
B: Allowing product entry under uniform prices [b]		
3. Expected variable profits (million $)		
Medtronic	[29.9, 32.7]	
St Jude Medical	[12.2, 14.4]	
Biotronik	[3.8, 5.9]	
4. Δ Expected total profits (%)		
Medtronic	[-13.7, -9.2]	
St Jude Medical	[-6.1, -1.2]	
Biotronik	[-1.8, 12.7]	
5. Expected hospital surplus (million $)	[87.2, 90.9]	
Δ (%)	**[-7.5,-3.6]**	
6. Δ Expected total surplus (%)	**[-8.4, -4.6]**	
7. MRI-safe ICD share	[0.87, 0.97]	
Δ (%)	**[-10.3,0]**	
8. Average inside good share	[0.16, 0.17]	
Δ (%)	**[-15.7, -10.5]**	

[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 the range of results for the equilibria under uniform pricing. Expected variable profits of the firms, 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. 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.
Expected profit and surplus measures are reported for the first period in 2019.

Results with product entry: Next, holding current product offerings fixed, I allow the manufacturers in my data to delay the exit of eight MRI-unsafe products (see section 1.7.1 for a recap). I find the set of equilibria that would exist for some fixed cost values in my estimated bounds. 23 possible equilibria exist. Under uniform pricing, the current set of product offerings exists as a possible equilibrium for a certain set of fixed cost values; when fixed costs for all 8 MRI-unsafe products are too high, no additional product will continue to be offered. In the remaining equilibria, at least one of these 8 products, and a maximum of two products, would continue to be offered in the first period of 2019. Table 1.5 shows that in 10 out of these 23 equilibria, an additional MRI-unsafe product of St Jude Medical and Biotronik would continue to be offered, and in 11 equilibria, one or two products of either St Jude Medical or Biotronik would continue to be offered. Interestingly, St Jude Medical and Biotronik are the two firms that price to their most inelastic consumers under uniform pricing, suggesting that they have the largest variation in brand loyalties between markets, and thus the most to gain from introducing an additional product. Figure 1.5 shows the distribution of the average prices of the products that were re-introduced by a firm (blue) in some equilibrium, and the average uniform prices of the products that were being offered by the same manufacturer (green) in that equilibrium. It shows that all the re-introduced products had a lower price than those that were being offered in the first period of 2019. Table 1.7 shows that when a manufacturer is the only one to introduce an additional MRI-unsafe product, the average prices of its existing MRI-safe products go up. Table 1.6 shows that when there is product entry by a rival, the average prices of a firm that has no entry drop.

Panel B from Table 1.8 reports the welfare results from these equilibria. 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 (table 1.7). 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 (table 1.6). Row 5 of Panel B of table 1.8 shows that allowing for additional MRI-unsafe products to be offered can offset hospital surplus losses from uniform pricing by up to 50%, as hospital welfare now only reduces by up to 3.6% relative to price discrimination. For about 6% of the hospitals in my sample, allowing for product entry reverses the welfare predictions of uniform pricing; specifically, these hospitals were facing welfare losses under uniform pricing when we held product offerings fixed, but when we endogenized product offerings we found that their surplus actually increased under uniform pricing. While the additional MRI-unsafe products cause an increase in hospital surplus, the share of ICDs purchased that are equipped with a superior technology drops by up to 10.3% (row 7 of table 1.8).

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. Endogenizing product offerings has an ambiguous effect on manufacturer profits. These effects depend upon which equilibrium we arrive at, and on the value of fixed costs at this equilibrium. There is only one equilibrium in which Medtronic

chooses to offer an additional product, and this equilibrium exists for a very small set of fixed costs for Medtronic. Thus, Medtronic is always weakly worse off relative to the fixed product offerings case, when we endogenize product offerings, because entry by one of its rival firms has a business-stealing effect and reduces its variable profits. St Jude Medical and Biotronik may be better or worse off relative to the fixed product offerings case depending on 1) which equilibrium they end up at and 2) the range of fixed costs for which this equilibrium exists. When Biotronik or St Jude Medical are the solo-entrant, they ends up being better off than they would be if we kept product offerings fixed. When both these manufacturers continue to offer an additional MRI-unsafe ICD, they may be better off if their fixed costs of doing so are low, but there are cases when both manufacturers end up in a prisoners-dilemma style equilibrium, in which they could both be better off if they chose not to offer an additional product, but given that the other manufacturer is offering an additional product it is optimal for each firm to do so. Thus, in some cases even when a manufacturer chooses to offer an additional product its profitability can drop below the fixed product offerings case.

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 always lower than the price discrimination case, but depending on the equilibrium we end up at, it may or may not be higher than the uniform pricing case with fixed product offerings.

1.8 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 have incentives to use products that are vertically differentiated in quality to indirectly price discriminate. They would do so by keeping 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 to some extent the expected hospital welfare losses from the higher prices due to uniform pricing. However, under these equilibria more patients would be implanted with older, inferior devices.

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 1.9.3 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.

1.9 Appendix

1.9.1 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

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

In this scenario manufacturers are allowed to third degree price discriminate.[25]

$$p_1^H = \theta_1$$

$$p_2^H = \theta_2$$

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

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

$$p_1^H = p_2^H = p_{c22} = \theta_{\mathbf{1}}$$

,

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

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

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.

[26] I also have data on CRT-D purchases, but I drop these due to the reasons outlined in footnote 11.

1.9.2 Data cleaning for demand estimation

My raw data has monthly purchases and prices of ICDs by 868 hospitals from 2014-2019.[26] 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 1.9), so this is a reasonable assumption.

- 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 (Bollmann et al., 2005).

  - The life-span of an ICD is 5-7 years. [27]

  - 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).

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

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:
  - 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

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

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.

1.9.3 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 1.9. 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 1.9: 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

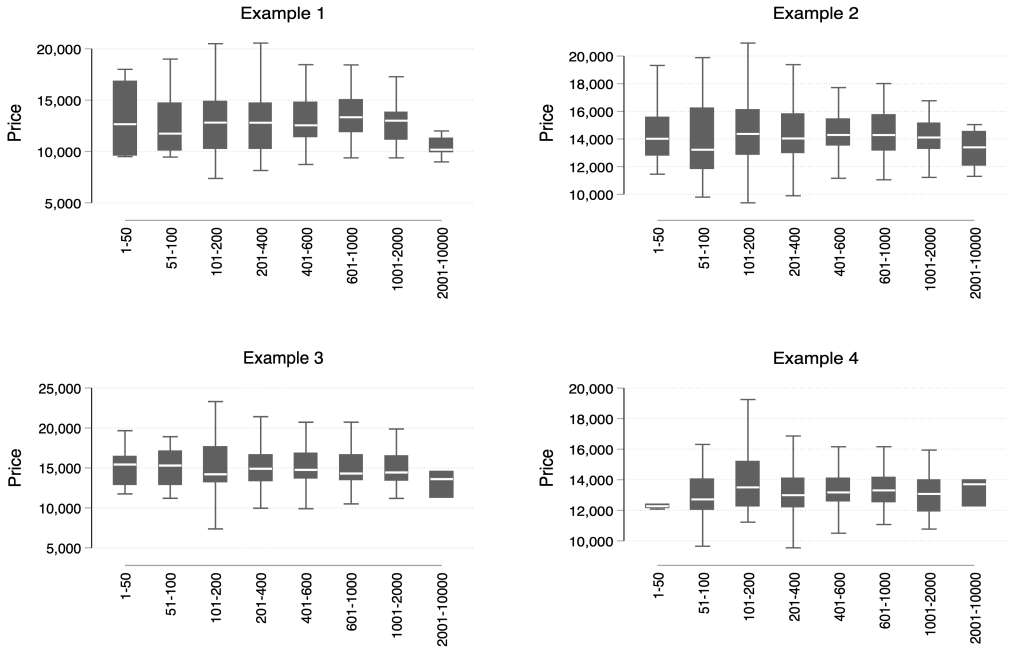
results of these regressions are in table 1.10 In all of these regressions, I find that a 1% increase in quantities purchased reduces prices by less than 0.01%. Thus, while quantity discounts do seem to exist in this industry, they do not seem to be substantial enough to explain the large variation in prices that I see in my data.

Table 1.10: 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.

Figure 1.6: 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

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 1.6 shows that the distribution 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 1.11.

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

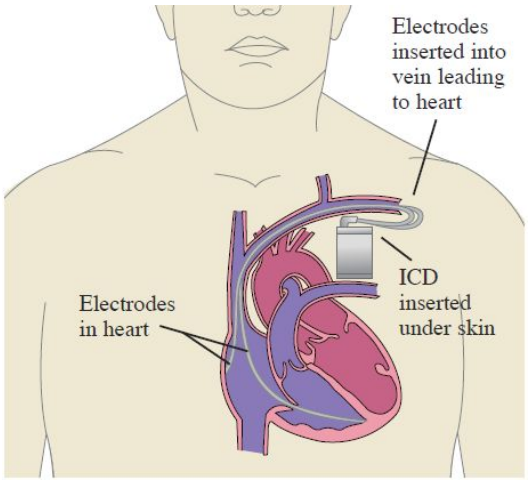
very concentrated, and sales representatives from each manufacturer are likely to be present in every hospital.

Table 1.11: 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.

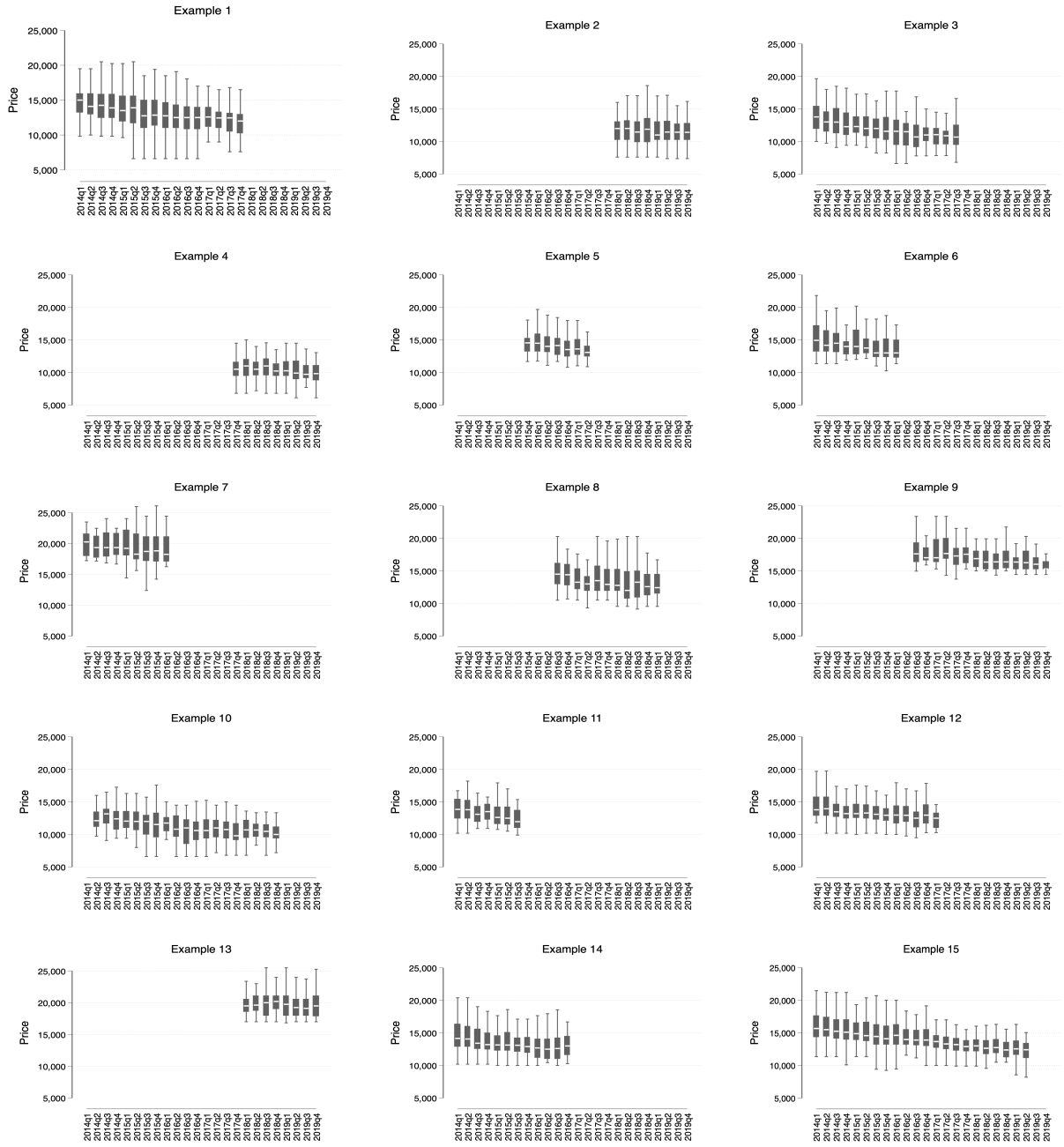
Figure 1.7: Picture of an ICD



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

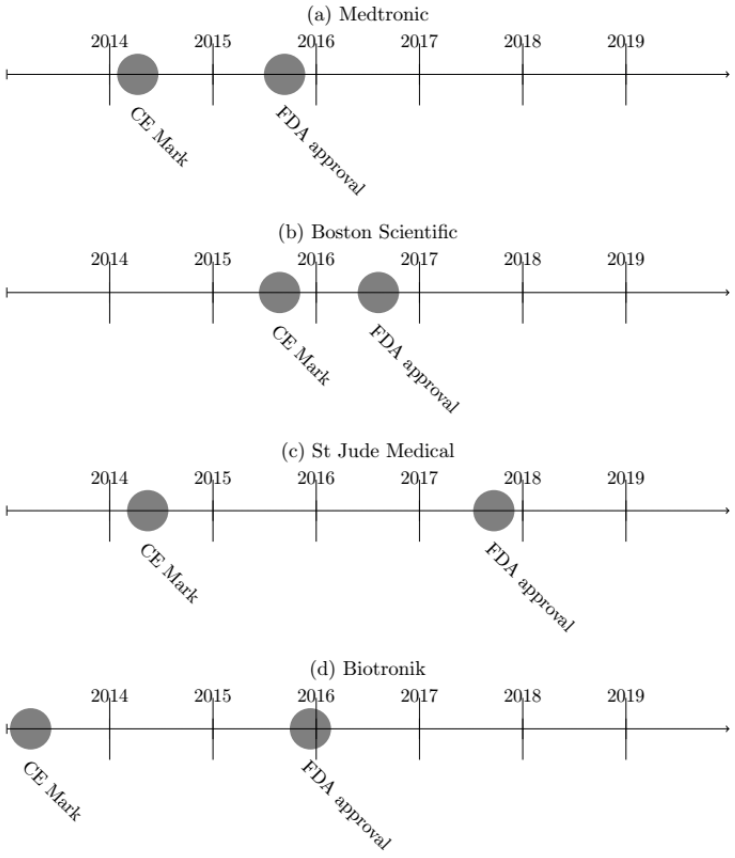
1.9.4 Additional figures and tables

Figure 1.8: 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 1.9: FDA approval timeline for MRI-safety feature



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 1.12: 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 1.13: Diversion

			Medtronic		St Jude Medical		Biotronik	
	MRI-safe	Outside	MRI-unsafe	MRI-safe	MRI-unsafe	MRI-safe	MRI-unsafe	MRI-safe
Medtronic	MRI-unsafe	0.35	0.13	0.13	0.08	0.08	0.08	0.05
	MRI-safe	0.33	0.10	0.19	0.07	0.12	0.09	0.09
St Jude Medical	MRI-unsafe	0.34	0.11	0.11	0.11	0.12	0.07	0.05
	MRI-safe	0.35	0.05	0.16	0.08	0.16		0.05
Biotronik	MRI-unsafe		0.09	0.12	0.10		0.33	
	MRI-safe	0.08	0.06	0.15	0.06	0.09		0.15

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

Table 1.14: Diversion - Full matrix

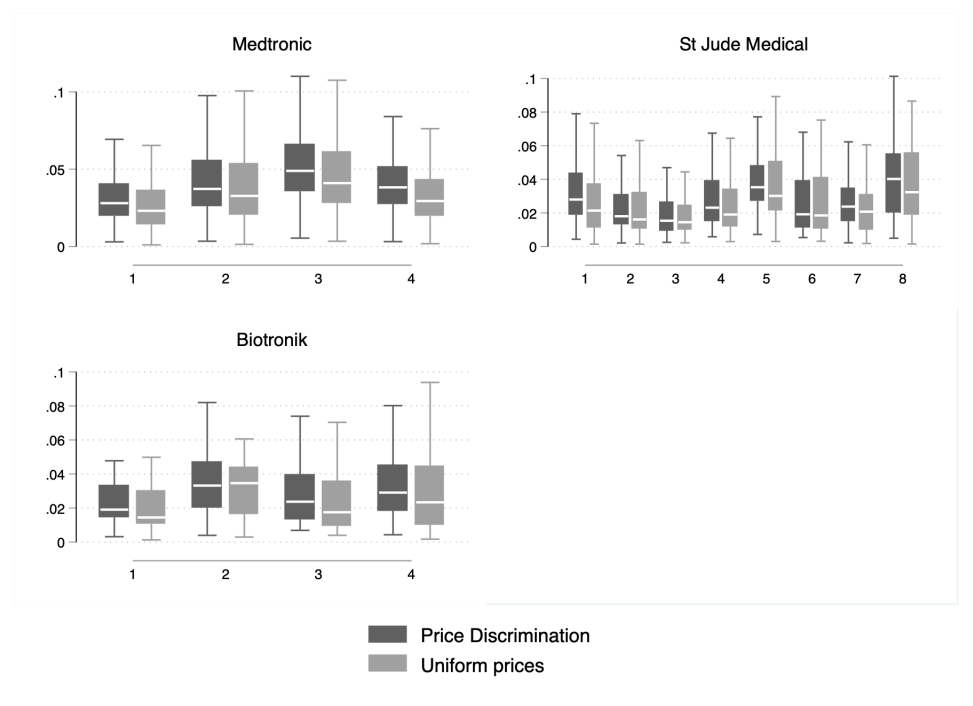
			Medtronic										St Jude Medical									
	Product	MRI-safe	A	B	C	D	E	F	G	H	I	J	A	B	C	D	E	F	A	B	C	D
Biotronik	A	No		0.06	0.07	0.15		0.09	0.13		0.12		0.13	0.06	0.07	0.14			0.33			
	B	Yes				0.06	0.09		0.07	0.22	0.18	0.14	0.08	0.04	0.05	0.06	0.10	0.09		0.30	0.07	0.06
	C	Yes		0.04		0.07	0.09	0.04	0.06	0.25	0.17	0.14	0.07	0.04	0.05	0.05	0.08	0.06		0.06	0.30	0.11
	D	Yes		0.05	0.01	0.08	0.10	0.05	0.08	0.24	0.16	0.12	0.08	0.04	0.06	0.07				0.04	0.09	0.31
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			0.02		0.04	0.06
	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			0.08			0.01
	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	0.08	0.06	0.06	0.07
	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				0.06	0.08	0.07
	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			0.12		0.03	0.07
	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			0.11	0.10	0.08	0.09
	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				0.11	0.15	0.13
	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	0.07	0.08	0.09	0.08
	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		0.07	0.08	0.07
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			0.06	0.05	0.05	0.07
	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	0.07	0.05	0.03	0.05
	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	0.06	0.05	0.05	0.06
	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			0.08	0.05	0.04	0.07
	E	Yes				0.06					0.20	0.14		0.08	0.08		0.34	0.15		0.05	0.04	
	F	Yes				0.04					0.17	0.12		0.07	0.07		0.17	0.35		0.06	0.04	

This table is the mean diversion matrix for products of the most popular brand from the 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 1.15: Fixed costs

Firm	Brand	Product	LB	UB
Biotronik	iforia	1	24,368	30,198
Biotronik	ilesto	1	18,306	30,198
Biotronik	ilesto	2	17,814	30,198
Biotronik	ilesto	3	15,564	30,198
Biotronik	ilesto	4	11,898	30,198
Biotronik	ilesto	5	9,738	30,198
Biotronik	ilesto	6	10,912	30,198
Biotronik	ilivia	1	8,364	18,559
Biotronik	intica	1	8,364	14,067
Biotronik	inventra	1	10,407	30,198
Biotronik	inventra	2	8,364	17,961
Biotronik	inventra	3	11,890	30,198
Biotronik	iperia	1	10,769	30,198
Biotronik	iperia	2	12,110	30,198
Biotronik	iperia	3	8,364	10,927
Biotronik	iperia	4	9,319	30,198
Biotronik	itrevia	1	13,382	30,198
Biotronik	itrevia	2	15,654	30,198
Biotronik	itrevia	3	10,120	30,198
Biotronik	lumax	1	19,890	30,198
Medtronic Plc	evera	1	15,928	26,867
Medtronic Plc	evera	2	13,635	26,867
Medtronic Plc	evera	3	4,778	19,211
Medtronic Plc	evera	4	14,490	26,867
Medtronic Plc	evera	5	17,578	26,867
Medtronic Plc	evera	6	4,778	26,805
Medtronic Plc	evera	7	15,333	26,867
Medtronic Plc	evera	8	14,257	26,867
Medtronic Plc	evera	9	14,949	26,867
Medtronic Plc	evera	10	15,929	26,867
Medtronic Plc	evera	11	21,483	26,867
Medtronic Plc	evera	12	10,823	26,867
Medtronic Plc	evera	13	20,916	26,867
Medtronic Plc	protecta	1	9,116	26,867
Medtronic Plc	protecta	2	11,336	26,867
Medtronic Plc	protecta	3	13,508	26,867
Medtronic Plc	protecta	4	15,786	26,867
Medtronic Plc	protecta	5	7,122	26,867
Medtronic Plc	protecta	6	9,187	26,867
Medtronic Plc	protecta	7	10,546	26,867
Medtronic Plc	protecta	8	13,106	26,867
Medtronic Plc	secura	1	18,503	26,867
Medtronic Plc	visia	1	4,778	19,401
Medtronic Plc	visia	2	4,778	14,077
Medtronic Plc	visia	3	12,530	26,867
St Jude Medical	ellipse	1	7,049	12,293
St Jude Medical	ellipse	2	12,231	15,392
St Jude Medical	ellipse	3	7,049	7,592
St Jude Medical	ellipse	4	9,020	15,392
St Jude Medical	ellipse	5	9,711	15,392
St Jude Medical	ellipse	6	7,049	11,206
St Jude Medical	ellipse	7	7,049	9,309
St Jude Medical	ellipse	8	11,457	15,392
St Jude Medical	ellipse	9	7,049	9,560
St Jude Medical	ellipse	10	13,623	15,392
St Jude Medical	fortify	1	20,202	15,392
St Jude Medical	fortify assura	1	11,299	15,392
St Jude Medical	fortify assura	2	11,477	15,392
St Jude Medical	fortify assura	3	8,911	15,392
St Jude Medical	fortify assura	4	11,410	15,392
St Jude Medical	fortify assura	5	7,049	12,570
St Jude Medical	fortify assura	6	7,049	15,114
St Jude Medical	fortify assura	7	9,168	15,392
St Jude Medical	fortify assura	8	7,049	15,392
St Jude Medical	fortify assura	9	7,049	10,644

Figure 1.10: Shares under counterfactual with no entry



This figure shows the expected shares of the products that were offered in the first period of 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.

Table 1.16: Elasticities

			Medtronic										St Jude Medical						Biotronik			
	Product	MRI-safe	A	B	C	D	E	F	G	H	I	J	A	B	C	D	E	F	A	B	C	D
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			0.14		0.24	0.34
	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			0.42			0.06
	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	0.41	0.31	0.34	0.33
	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				0.28	0.40	0.35
	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			0.57		0.18	0.35
	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			0.53	0.68	0.44	0.50
	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				0.47	0.67	0.56
	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	0.31	0.35	0.41	0.38
	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		0.34	0.38	0.33
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			0.33	0.29	0.27	0.33
	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	0.42	0.28	0.20	0.27
	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	0.31	0.27	0.27	0.33
	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			0.39	0.33	0.25	0.38
	E	Yes				0.32					1.13	0.80		0.29	0.28		-4.49	0.52		0.29	0.22	
	F	Yes				0.25					1.03	0.75		0.29	0.29		0.78	-4.34		0.35	0.22	
Biotronik	A	No		0.26	0.37	0.78		0.52	0.63		0.73		0.67	0.22	0.33	0.65			-5.19			
	B	Yes				0.31	0.45		0.41	1.72	1.04	0.83	0.36	0.18	0.24	0.25	0.48	0.37		-5.27	0.39	0.32
	C	Yes		0.21		0.35	0.41	0.20	0.31	1.80	1.00	0.77	0.32	0.17	0.25	0.22	0.40	0.27		0.34	-5.39	0.56
	D	Yes		0.24	0.05	0.43	0.47	0.28	0.46	1.84	0.95	0.73	0.39	0.17	0.28	0.27				0.25	0.50	-5.15

This table is the mean elasticities matrix for products of the most popular brand from the 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 0.60%

2 Chapter 2: Drug information diffusion through acquisitions

(Coauthored with Motaz Al-Chanati)

2.1 Introduction

In the pharmaceutical and medical devices industries, physician detailing is an important form of marketing for branded drugs and devices. Physician detailing often involves transfers from a branded drug or device manufacturer to a physician. More than 90% of these transfers take place in the “Food & Drink" category. Marketing in this category typically involves an in-person meeting between a pharmaceutical/device sales representative and a physician, in which the sales representative buys the physician a meal and talks to the physician about the drug over the course of the meal (Ornstein, 2011). Physician-sales representative networks are strong and long-term in this industry (Grundy et al., 2018), and the marketing (detailing) meals provided to physicians by sales representatives have been shown to affect physician behavior (Grennan et al., 2021). The Physician Payments Sunshine Act of 2010 made it mandatory for manufacturers and physicians to disclose these transfers, and data on these transfers has been public since August, 2013.

When the ownership of a drug changes, the composition of sales representatives that market this drug also changes. For example, when the ownership of a drug is transferred from one firm to another, it gains access to the sales representatives of the acquiring firm, and loses access to the sales representatives of its initial owner (the target firm). Similarly, when an entire firm is acquired by another, the acquired drugs gain access to the acquiring parent’s sales representatives, and may or may not

lose the target firm's sales representatives. Given that pharmaceutical sales representatives have long-term relationships with physicians, gaining (losing) access to sales representatives can be thought of as gaining (losing) access to the marketing networks of a firm. Further, given that physician detailing, or interactions between physicians and sales representatives affect prescription behavior by physicians, a change in the marketing networks of a firm can have implications for the prescription behavior of physicians, and can thus affect patient welfare.

In this paper, we systematically compile a list of 10 drug acquisitions, and we use a detailed dataset on marketing meals provided to physicians at the physician-drug-quarter level, and Medicare Part D prescriptions for each drug at the physician-drug-year level to analyze the changes in marketing behavior and prescription behavior for a drug after it faces an ownership change.

In our first set of regressions, we find that after the acquisition takes place, an acquired drug is disproportionately more likely to be marketed to physicians that the acquiring parent had prior relationships with. This result suggests that firms leverage their existing relationships with physicians to market their newly acquired drugs. In our second set of regressions, we find that after an acquisition takes place, an acquired drug is disproportionately less likely to be marketed to physicians that the target (former owner) firm has prior relationships with. This suggests that on average, acquired drugs lose the target firm's marketing networks. In our third set of regressions, we find that after a drug is acquired from a target firm, there is no significant change in the acquiring firm's likelihood of marketing its other drugs to physicians that belong to the target firm's marketing networks. This result suggests that on average, firms do not gain the target network's physician-sales representative

relationships. There is some heterogeneity in this result depending on the type of acquisition that took place. When the acquisition is of an entire firm with a large marketing network, we see increases in the acquiring firm's likelihood of marketing its other drugs to physicians that belong to the target firm's marketing networks. Overall, our results indicate that marketing behavior for an acquired drug changes significantly after an acquisition takes place, with a shift in marketing toward the acquiring firms' networks, and a shift away from the target firms' networks.

Next, we show that these shifts in marketing translate closely to physician prescription behavior. First, we document a result that has already been established in the literature; prescriptions are positively associated with detailing. Next, we show that prescriptions increase disproportionately among physicians that had pre-existing relationships with the acquiring firms, and decline among physicians that had pre-existing relationships with the target firm. These results hold along the intensive (number of prescriptions per physician-year) and the extensive (probability of a physician-year having positive prescriptions) margin.

Our results have some limitations. First, we our paper is entirely descriptive. Our regressions do not account for the fact that an acquisition itself is endogenous, i.e. it could be motivated by the synergies between the drug and sales representative networks of the acquiring firm. For example, one of the drug acquisitions in our sample was of an oncology drug, and it took place because the acquiring parent already had a strong oncology portfolio.[28] Second, our prescription data comes from Medicare Part D. Some of the drugs in our sample are not covered for certain indications by Medicare Part D, and some drugs may be covered, but are not usually prescribed to

[28]There were no competition concerns for this acquisition, as this drug was in a different class.

the elderly. Due to these limitations, we are unable to capture the universe of prescriptions for each drug. Third, the only interactions between sales representatives and physicians we capture are through meals. It's possible that they have other marketing interactions that we do not observe. Finally, we do not comment on how this ownership change, which is associated with a change in marketing and prescriptions changes consumer (patient) welfare. We believe the answer to this question lies in how the informative and persuasive components of detailing for a drug change following its acquisition, and we leave this quantification exercise to future work.

The "killer acquisitions" story, in Cunningham et al. (2021), sheds light on one reason why pharmaceutical acquisitions may take place; to kill future competition. We provide evidence on a different reason why such acquisitions may take place. Our results suggest that even when there is no competitive threat that may incentivize an acquisition, there may be marketing synergies from acquiring a drug that come from giving these drugs access to the acquiring parent's marketing networks. There is a vast literature on the effects of advertising in the pharmaceutical industry. Some of the most salient papers that measure the effects of physician detailing on prescriptions are Carey et al. (2020) and Grennan et al. (2021). Agha and Zeltzer (2019) measures the spillovers in detailing on a physician's peer networks. Sinkinson and Starc (2019) measures the effects of direct-to-consumer advertising on demand. To our knowledge, we are the first to study drug acquisitions and detailing, and to document a shift in detailing and prescription behavior for a drug after its acquisition.

The rest of this paper is organized as follows. In Section 2.2, we describe our data sources and show some summary statistics from each data source. In Section 2.3, we show some descriptive statistics about physician-firm relationships in this industry.

Section 2.4 has our results on physician detailing after an acquisition and Section 2.5 has our results on prescriptions. In Section 2.6 we discuss our results, and we conclude in Section 3.6.

2.2 Data and Summary Statistics

2.2.1 Drug acquisitions

Our first source of data is S&P Capital IQ. From this database, we collected the list of drug acquisitions that took place in 2015-2016 in the "Pharmaceuticals" industry classification. We then manually removed drug acquisitions which 1) Have no transaction in Open Payments from 2014-2018. 2) No Medicare prescriptions from 2014-2018. 3) Were generic. 4) Lost patent protection during this period. 5) Were FDA approved after 2012.[29] 6) Had generic entry during the period of analysis.[30] 7) Got discontinued in 2014-2018. 8) Had fewer than 500 detailing transactions per quarter, in all quarters from 2014-2018. We are then left with 10 drug acquisitions that took place in 2015-2016 (Table 2.1).[31] In this list, some acquisitions were of the entire firm, while some were a transfer of ownership between firms. For example, Actavis acquired Allergan, and as a result of this acquisition gained the drugs Combigan and Botox. Some examples of firms exchanging drugs (rather than acquiring each other) in our sample are of GlaxoSmithKline and Novartis. GlaxoSmithKline acquired Menveo from Novartis, and Novartis acquired Votrient and Promacta from

[29] We remove these drugs because the sudden spike in marketing right after they receive approval might confound the effects of an acquisition.

[30] This is because marketing payments for a drug usually drop dramatically after generic entry takes place. This might confound the effects of an acquisition.

[31] I exclude Valeant and Salix from this list of acquisitions, as Salix was a firm that specialized in gastroenterology drugs, and primarily detailed to gastroenterologists while Valeant specialized in eye health and neurology drugs. The results in this paper are robust to including this acquisition.

GlaxoSmithKline. Nucynta was divested to Depomed by Janssen in 2015. None of the acquisitions in the list created any competition concerns.

Table 2.1: Drug acquisitions

Buyer	Target	Acquired Drug	Date
actavis	allergan	combigan botox	17mar2015
arbor	xenoport	horizant	01jul2016
depomed	janssen	nucynta	02apr2015
endo	auxilium	xiaflex	29jan2015
glaxosmithkline	novartis	menveo	02mar2015
horizon	crealta	krystexxa	13jan2016
novartis	glaxosmithkline	votrient promacta	02mar2015
otsuka	avanir	nuedexta	12jan2015

This table has the list of drug acquisitions we use in our analysis. The Buyer is the acquiring firm, and the Target is the firm the each drug is acquired from. The date is Actavis changed its name to Allergan after acquiring it.

2.2.2 Physician detailing

Our second source of data is CMS Open Payments (Med, 2018). We have transaction-level data on physician detailing in the "Food and Beverage" (meal) category. [32] This category constitutes about 90% of transactions in this industry. From this database, we have information the dollar amounts of each meal at the physician-drug level. We aggregate this data to the quarter-physician-drug level. Table 2.2 shows, for each drug, the average value of a meal, the total meal payments (in US $) provided in 2014-2018, the total number of meals provided, and the number of physicians these

[32] In the rest of this paper, I will refer to a transaction in this category as a meal.

meals were provided to. The average meal value ranges from $16-$43. There is a large variation in the total ($) meal payments, total number of meals, and the number of physicians that are provided these meals between drugs. For example, meal payments for Botox exceeded $4 million, while payments for Promacta were close to $0.5 million. Similarly, the number of physicians receiving meals over this period ranges from 6,365 to 32,162.

Table 2.2: Summary statistics

Drug	Avg meal value ($)	Total payments ($)	# transactions ($)	# Physicians
botox	23	4,188,188	180,988	32,162
combigan	43	959,896	22,101	9,383
horizant	18	1,033,760	56,539	15,590
krystexxa	30	938,643	30,872	9,499
menveo	18	737,024	40,367	19,779
nucynta	19	2,016,118	105,248	19,110
nuedexta	22	4,024,034	180,342	36,452
promacta	16	512,717	31,827	6,729
votrient	16	532,416	32,650	6,365
xiaflex	22	1,155,414	52,418	11,236

This table shows 1) The average value of a transfer from a manufacturer to a physician.
2) Total spending on meals in 2014-2018.
3) Average number of transactions in 2014-2018.
4) Number of unique physicians that received a meal in 2014-2018.

2.2.3 Prescriptions

Our third source of data is the Medicare Part D Prescriber Public Use Files (CMS, 2018). From this database, we have the total number of 30-day standardized prescription fills at the drug-physician-year level.[33] This database has some limitations for our context. First, it only contains claims for people covered by Medicare Part

[33]The number of 30-day standardized prescription fills are calculated by dividing the number of days for which the drug is prescribed by 30.

D, i.e. people aged 65 and above. However, some of the drugs that were acquired are not usually prescribed to the elderly. For example, Menveo is a vaccine used to prevent invasive meningococcal disease and is approved by the FDA for use up to 55 years of age.[34] Table 2.3 shows that only 108 physicians prescribed Menveo under Medicare Part D in 2014-2018. Second, some drugs are not covered by Medicare for certain indications. For example, Botox is covered by Medicare Part D for certain indications, but not for cosmetic use. Hence, we see that while 32,162 physicians received marketing payments for Botox (2.2), only 1,206 physicians prescribe it under Medicare Part D.

Table 2.3: Summary statistics

Drug	# Physicians	# 30-day prescription fills
botox	1,206	172,831
combigan	34,252	7,393,346
horizant	1,907	73,583
krystexxa	26	573
menveo	108	4,020
nucynta	8,746	561,032
nuedexta	16,894	1,768,602
promacta	1,677	57,427
votrient	1,556	48,840
xiaflex	23	343

This table shows 1) The number of physicians that prescribe each drug under Medicare Part D in 2014-2018 2) Total number of 30 day prescription fills for each drug in 2014-2018.

2.2.4 Drug classes

Our final source of data is www.drugs.com. From this source, we collected the drug class for each drug that was acquired, where a drug class is assigned based on the

[34]https://www.rxlist.com/menveo-drug.htm

chemical in the drug or the condition the drug is used to treat. Table 2.4 shows, for each acquired drug, the number of other drugs in the same class as the acquired drug.

Table 2.4: In-network and out-of network physicians, and number of drugs in the acquired drug class

Drug	Number of Physicians		Drugs in same class
	In-network	Out-of-network	
botox	20,232	18,077	6
combigan	20,232	11,067	6
horizant	32,730	41,418	3
krystexxa	26,571	15,945	3
menveo	69,792	21,011	5
nucynta	7,646	34,342	21
nuedexta	24,137	14,576	5
promacta	97,076	924	2
votrient	97,076	3,420	10
xiaflex	11,197	5,549	5

2.3 Physician-firm relationships

We show suggestive evidence that lends credibility to the idea that physicians and pharmaceutical sales representatives have long term relationships, and that there may be returns to scale from detailing the same physician for multiple drugs. We show that: 1) conditional on receiving a meal in at least one quarter from a firm, physicians receive meals from the same firm in multiple quarters, and 2) conditional on receiving a meal in at least one quarter from a firm, many physicians receive payments for multiple drugs belonging to this firm.

In Figure 2.1, we restrict our analysis to the buyer, or acquiring firms. The top panel of Figure 2.1 plots the distribution of the number of quarters in which a physician receives a meal from a firm, conditional on receiving at least one meal from

this firm in 2014-2018. We see that if a physician receives a meal from a firm, they always receive a meal in multiple quarters. The bottom panel of this figure plots the number of drugs of a firm for which a physician receives a meal, conditional on the physician receiving a meal for at least one drug of that firm in 2014-2018. This figure shows that more than 50% of physicians that receive a meal for at least one drug of a firm, receive meals for multiple drugs of the firm.

2.4 Physician detailing

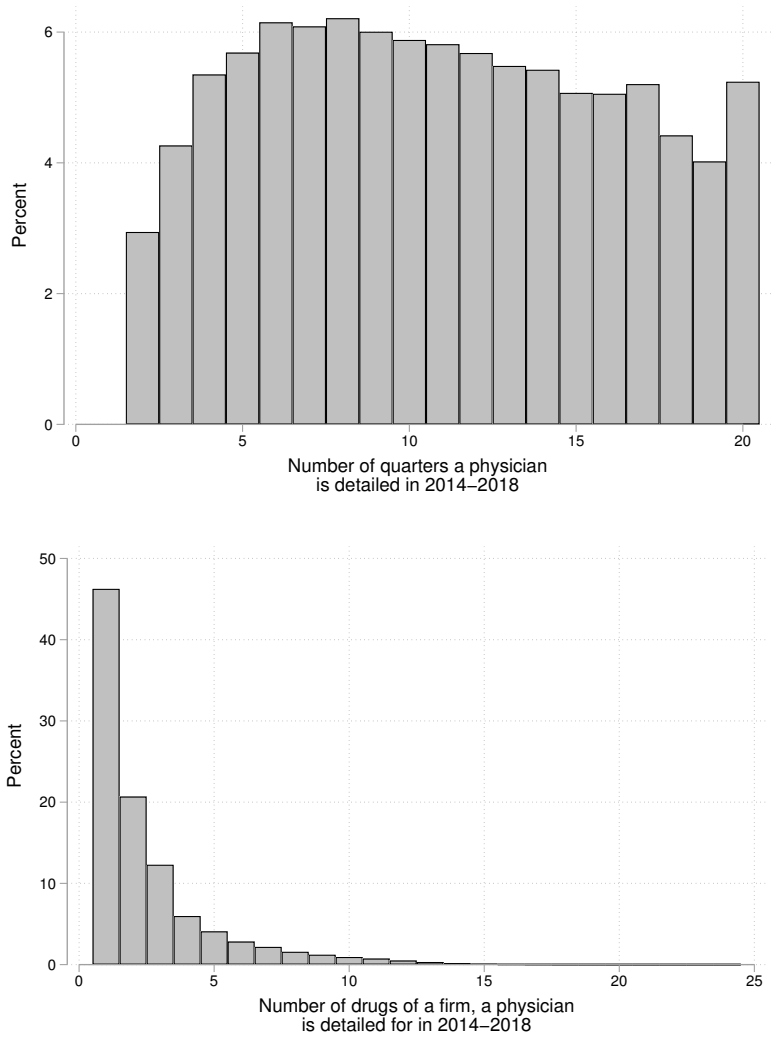
In this section, we first show that on average, aggregate detailing increases for the 10 acquired drugs after they are acquired. However, there is a lot of variation between the different drugs, with detailing increasing for some drugs after their acquisition and decreasing for others. Next, we show that there is a shift in the detailing strategy for a drug after it is acquired. First, an acquired drug gains access to the marketing networks of an acquiring firm. Second, an acquired drug loses access to the marketing networks of the target firm. Third, on average, acquiring firms do not acquire the marketing networks of the target firms. However, there is some degree of variation in this result depending on the type of acquisition (i.e. whether a single drug was acquired from a firm or the whole firm was acquired).

2.4.1 Aggregate detailing

We aggregate our data to the drug-quarter level, and estimate the following regression for the set of drugs in Table 2.1:

$$log(1 + y_{jt}) = \beta_0 + \beta_1 post_{jt} + \theta_j + \theta_t + \epsilon_{jt} \tag{8}$$

Figure 2.1: Physician-firm relationships



The top panel of this figure shows the distribution of the number of quarters in which a physician receives a meal from a firm, conditional on receiving at least one meal from this firm in 2014-2018. The bottom panel of this figure shows the number of drugs belonging to a firm for which a physician receives a meal, conditional on receiving at least one meal for a drug belonging to this firm in 2014-2018.

Define t_{closed} to be the quarter the acquisition was closed. Then $post_{jt} = 1$ if $t \geq t_{closed}$, and 0 otherwise. θ_j and θ_t are drug and time fixed effects. y_{jt} is:

1. The total $ amount spent on meals for drug j in quarter t.

2. The total number of meals provided for drug j in quarter t.

3. The total number of physicians detailed for drug j in quarter t.

From table 2.5, we see that on average, expenditure on meals, the number of meals provided, and the number of physicians detailed nearly doubled after a drug was acquired. However, these averages mask considerable heterogeneity between drugs. Figure 2.6 in the Appendix shows that aggregate detailing expenditures increased for some drugs after their acquisition, and declined for others.

Table 2.5: Change in aggregate detailing after acquisition

	Log(amount ($))	log(# transactions)	log(# physicians)
Post	0.935*	0.961***	0.789**
	(0.375)	(0.203)	(0.187)
Constant	10.064***	6.985***	6.761***
	(0.262)	(0.142)	(0.130)
R^2	0.805	0.721	0.696
N	200	200	200
Drug FE	Y	Y	Y
Time FE	Y	Y	Y

This table shows the results from the regression in equation 8.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the drug level.

2.4.2 Shift in marketing strategies after an acquisition

Shift toward the acquiring firm's marketing networks: In this subsection, we show that an acquired drug gains access to the marketing networks of its acquiring firm. We first define two sets of physicians for each drug that was acquired:

1. **In-network physicians:** For each acquired drug, in-network physicians are defined to be the set of physicians that received meals from the acquiring firm before the acquisition. These physicians are assumed to already have a relationship with the sales representatives belonging to the acquiring firm prior to the acquisition, and hence are called in-network physicians.

2. **Out-of-network physicians:** Out-of-network physicians are defined to be the set of a physicians that *did not* receive meals from the acquiring firm prior to the acquisition, but received meals for *some drug belonging to the same class as the acquired drug, prior to its acquisition.*[35] These physicians are assumed to have no relationship with the acquiring firm's sales representatives, prior to the acquisition.

The first two columns of table 2.4 show the number of in-network and out-of-network physicians for each drug.

For each drug, we restrict the set of physicians to include only in-network and out-of-network physicians. Then, for each acquired drug we have a balanced panel at the physician-quarter level, with information on whether a physician received a meal in a quarter for that drug, and on whether or not that physician was in-network. We estimate the following regression separately for each acquired drug j:

[35]The idea behind restricting the out-of-network physicians to include relevant physicians, i.e

$$\text{Detailed}_{pt} = \beta_0 + \text{in-network}_p + \beta_x \text{in-network}_p \times \text{post}_t + \text{post}_t + \theta_p + \theta_t + \epsilon_{pt} \quad (9)$$

where $\text{Detailed}_{pt} = 1$ if physician p receives marketing payments for the acquired drug j in quarter t, and 0 otherwise, $\text{in-network}_p = 1$ if the physician p is in-network for the acquirer of drug j, and $\text{in-network}_p = 0$ if the physician is out-of-network. θ_p captures physician fixed effects, and θ_t captures time fixed effects.

Our coefficient of interest for each drug is β_x. β_x and its 95% confidence interval has been plotted for each drug separately in Figure 2.2. We see that the coefficient β_x is positive and significant for all the 10 drugs in our analysis. In words, after a drug acquisition, in-network physicians are more likely to receive a meal for the acquired drug relative to out-of-network physicians. The magnitude of this coefficient varies; for some drugs, after an acquisition, the probability of an in-network physician receiving a meal relative to an out-of-network one increases by less than 0.01, while for others it increases by more than 0.15.

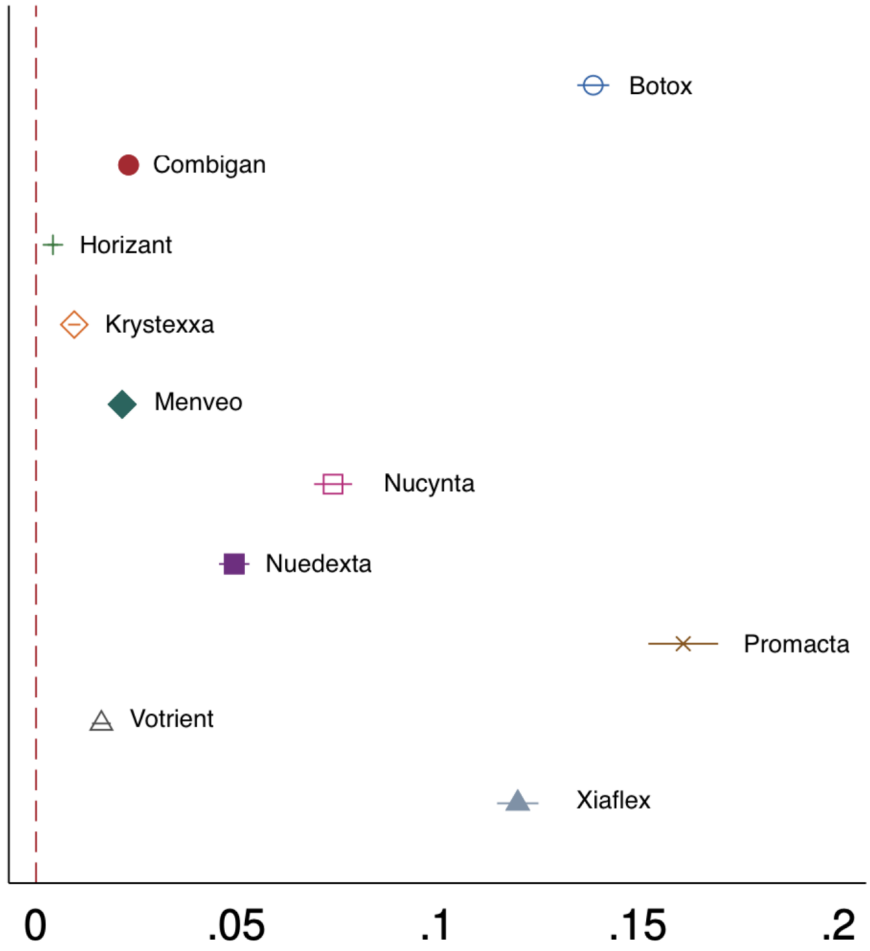
Next, we pool all the drugs together to form a drug-physician-quarter panel. We then estimate the following regression:

$$\text{Detailed}_{pjt} = \beta_0 + \beta_1 \text{in-network}_{pj} + \sum_{t=-4}^{t=8} \beta_t^1 \text{in-network}_{pj} \times T_t + \theta_t \times \theta_j + \theta_t \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjt} \quad (10)$$

$\text{Detailed}_{pjt} = 1$ if physician p receives a meal for acquired drug j in quarter t,

physicians that receive meals for drugs that are similar to the acquired drug.

Figure 2.2: Plotting β_x from equation 9



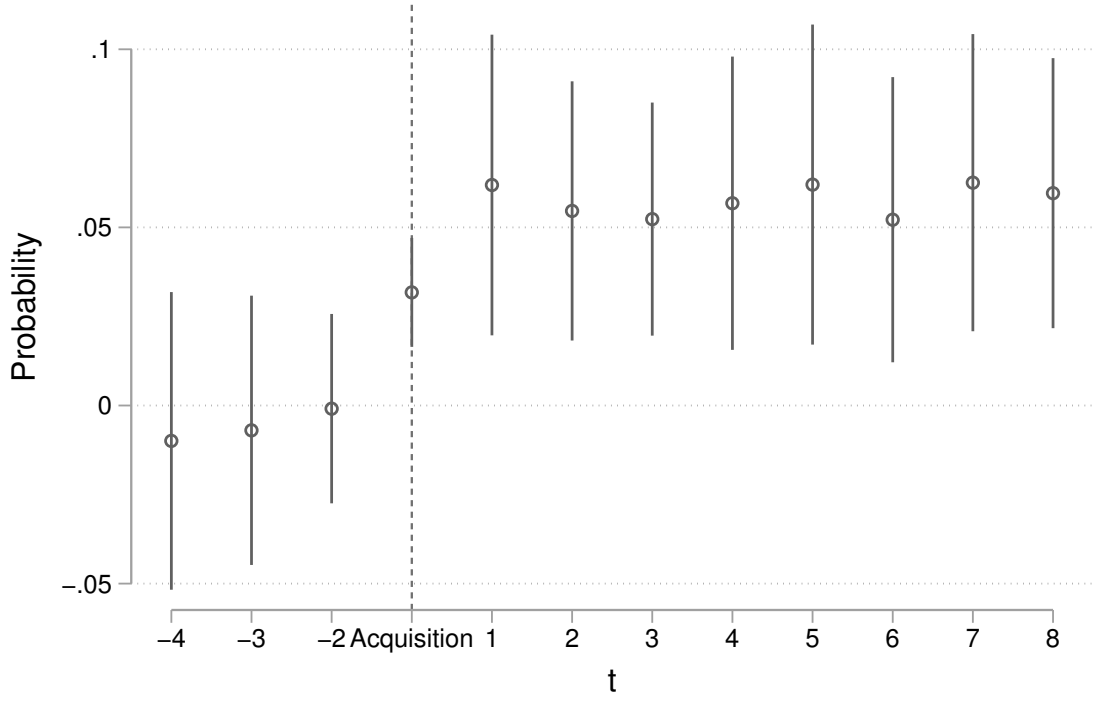
β_x from equation 9, and its 95% confidence interval has been plotted for each drug separately in this figure. The name of the drug is next to each plot.

in-network$_{pj}$ = 1 if physician p is in the marketing network of the acquirer of drug j, and 0 otherwise. T_t is a set of dummy variables that go from -4 (4 quarters before the acquisition) to 8 (8 quarters after the acquisition). $T_t = 0$ in the quarter of the acquisition. θ_j denotes drug fixed effects, θ_t denotes time fixed effects, and θ_p denotes physician fixed effects. Thus, in the full specification, we account for drug-time fixed effects, physician-time fixed effects and physician-drug fixed effects. Drug-time fixed effects help us account for aggregate trends in detailing for a drug, physician-time fixed effects help us account for the fact that some hospitals may change their policies to discourage or limit physician-sales representative relationships over this period. Physician-drug fixed effects allow us to account for the fact that some physicians are detailed more for some drugs.

Our coefficient of interest is β_t^1. We exclude T_t = -1, i.e. we make one quarter before the acquisition our reference category. Thus, β_t^1 tells us, in each period, whether the difference in the probability of detailing an in-network physician and an out-of-network physician, for an acquired drug, is statistically significantly different from what it was one quarter before the acquisition took place.

β_t^1 from equation 10, along with its 95% confidence intervals have been plotted in Figure 2.3. This figure shows us that in the 2, 3, and 4 quarters prior to the acquisition, the difference in the probability of an in-network physician and an out-of-network physician receiving a meal is not significantly different from this difference one quarter prior to the acquisition. However, after the acquisition, this difference jumps up, i.e. in-network physicians are disproportionately more likely to receive a detailing meal for the acquired drug. One quarter after an acquisition, the difference in the probability of receiving a meal between in-network and out-of-network

Figure 2.3: β_t^1 from equation 10, along with 95% confidence intervals.



This figure plots β_t^1, and its 95% confidence intervals from equation 10. The X-axis has T_t and the Y-axis has β_t^1.

physicians is about 6 percentage points higher than this difference one quarter before the acquisition. This effect is the strongest one quarter after the acquisition takes place. The regression corresponding to Figure 2.3 is in column (4) of Table 2.13 in the Appendix. Figure 2.7 in the Appendix plots the raw probabilities of in-network and out-of-network physicians receiving detailing for the acquired drug, and we see that these results are driven by the probability of an in-network physician receiving detailing for the acquired drug going up, and the probability of an out-of-network physician receiving detailing for the acquired drug going down.

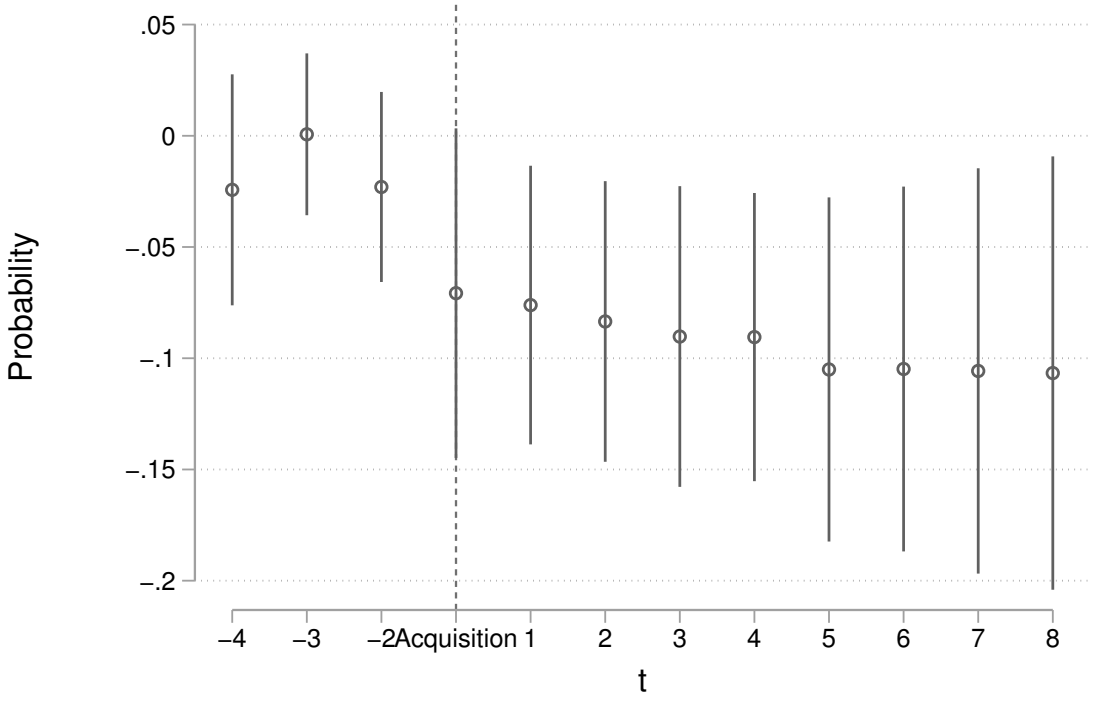
Shift away from the target firm's marketing networks: In this subsection, we show that an acquired drug loses access to the marketing networks of the target firm. For each drug that was acquired, we define two sets of physicians:

1. **Target-network physicians:** For each acquired drug, target-network physicians are defined to be the set of physicians that received meals from a target firm before the acquisition took place. These physicians are assumed to already have a relationship with the sales representatives belonging to the target firm prior to the acquisition, and hence are called target-network physicians.

2. **Target-out-of-network physicians:** Target-out-of-target-network physicians are defined to be the set of a physicians that *did not* receive meals from the target firm prior to the acquisition, but received meals for *some drug belonging to the same class as the acquired drug, prior to its acquisition.*

The first two columns of table 2.12 in the Appendix show the number of target-in-network and target-out-of-network physicians for each acquired drug. Figure 2.10 in the Appendix has Venn Diagrams which show the overlap between in-network and target network physicians. For each acquired drug, we restrict the set of physicians to include only target-network and target-out-of-network physicians. Then, for each acquired drug we have a balanced panel at the physician-quarter level, with information about whether or not a physician received detailing for the acquired drug in a quarter, and on whether or not the physician belonged to the target firm's marketing network. We pool the data for all the acquired drugs to create a panel at the

Figure 2.4: β_t^2 from equation 11, along with 95% confidence intervals.



This figure plots β_t^2, and its 95% confidence intervals from equation 11. The X-axis has T_t and the Y-axis has β_t^2.

drug-physician-quarter-level, and estimate the following regression:

$$\text{Detailed}_{pjt} = \beta_0 + \sum_{t=-4}^{t=8} \beta_1 \text{Target-network}_{pj} + \beta_t^2 \text{Target-network}_{pj} \times T_t + \theta_t \times \theta_j + \theta_t \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjt} \tag{11}$$

Again, $\text{Detailed}_{pjt} = 1$ if physician p receives a meal for drug j in quarter t, and 0 otherwise. $\text{Target-network}_{pj} = 1$ if physician p is in the marketing network of the initial owner, or target firm of drug j, and 0 otherwise. T_t is a set of dummy

variables that go from -4 (4 quarters before the acquisition) to 8 (8 quarters after the acquisition). $T_t = 0$ in the quarter of the acquisition. θ_j denotes drug fixed effects, θ_t denotes time fixed effects, and θ_p denotes physician fixed effects. Similar to equation 10, in the full specification, we account for drug-time fixed effects, physician-time fixed effects and physician-drug fixed effects.

Our coefficient of interest is β_t^2. We exclude T_t = -1, i.e. we make one quarter before the acquisition our reference category. Thus, β_t^2 tells us, in each period, whether the difference in the probability of detailing target-network and target-out-of-network physicians is statistically significantly different from this difference one quarter before the acquisition took place.

β_t^2 from equation 11, along with its 95% confidence intervals has been plotted in Figure 2.4. This figure shows us that in the 2, 3, and 4 quarters prior to the acquisition, the difference in the probability of a target-network physician and an target-out-of-network physician receiving a meal is not significantly different from this difference one quarter prior to the acquisition. However, after the acquisition, this difference jumps down, i.e. target-in-network physicians are less likely to receive a detailing meal for the acquired drug. One quarter after an acquisition, the difference in the probability of receiving a meal between target-network and target-out-of-network physicians is about 7 percentage points lower than this difference one quarter before the acquisition, and this difference increases (in absolute values) over time, suggesting that the shift away from target-firm physicians becomes more pronounced with time after the acquisition. The regression corresponding to Figure 2.4 is column (4) of Table 2.14 in the Appendix. Figure 2.8 shows that these results are driven both by a decline in detailing to target-network physicians and an increase in detailing to target

out-of-network physicians. One might be concerned that if the target out-of-network physicians include in-network physicians for the acquiring firm, this result is driven by the increase in detailing to the acquiring firm's in-network physicians. Thus, I separately estimate equation 11, excluding from this analysis in-network physicians of the acquiring firm. The results of this regression are in Figure 2.9 in the Appendix.

Are the target firm's marketing networks acquired? In this subsection we test whether a target firm's marketing networks are acquired. One way to test this is to quantify whether physicians that belonged to the marketing networks of the target firm received greater detailing for the acquiring firm's *other* drugs (drugs that were not acquired), after the acquisition.

In this section, we restrict our analysis to target-network physicians of each drug. We also restrict the analysis to all other drugs that belong to the acquiring firm, i.e. all drugs that belong to the acquiring firm except for the acquired drugs. For each such drug and physician, we construct a physician-quarter panel of detailing. We then pool the data for all the drugs and estimate the following regression:

$$\text{Detailed}_{pjt} = \beta_0 + \sum_{t=-4}^{t=8} \beta_t^3 T_t + \theta_t \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjt} \tag{12}$$

Again, we assume that the base period is T = -1, i.e. one quarter before the acquisition. Figure 2.5 plots β_t^3, along with 95% confidence intervals from this regression. From Figure 2.5, we see that on average, the probability that a target-network physician receives detailing for the acquiring firm's drugs does not change significantly after an acquisition. The results for the regression in equation 12 are in Table 2.15 in the Appendix.

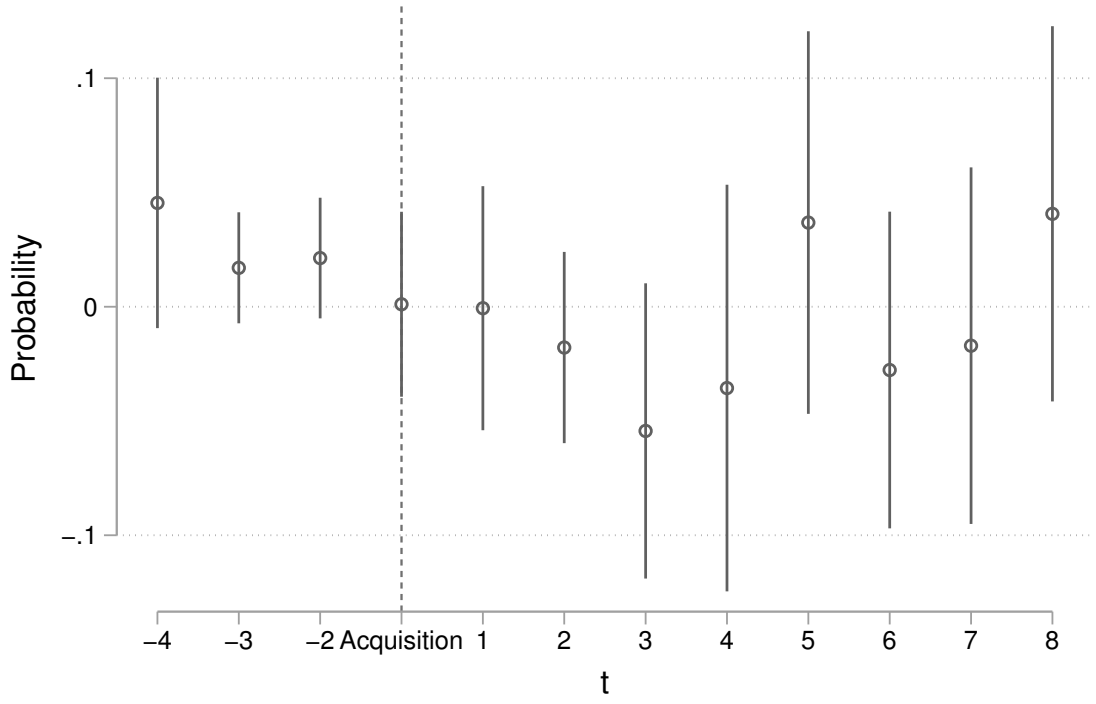
Heterogeneity: The results from the pooled regression mask some heterogeneity between acquisitions. These results vary by drug, and seem to depend on the type of acquisition that took place. In table 2.6, we report the unconditional probability that a target-network physician receives detailing for the acquiring firm's other (non-acquired) drugs, before and after the acquisition. In some cases, when a full firm is acquired by another firm (such as Actavis' acquisition of Allergan, in which Botox and Combigan were acquired), the target firm's physicians do seem to join the networks of the acquiring firm, as the probability of target-network physicians receiving meals for the acquiring firm's drugs goes up by more than 300%. However, this does not seem to generally be the case when a full firm is acquired. In some cases, such as the acquisition of Crealta by Horizon (in which Krystexxa was acquired), we see a slight decline in this probability. [36] Interestingly, in cases where drugs were merely exchanged between firms, such as the acquisition of Menveo from Novartis by Glaxosmithkline, and the acquisition of Votrient and Promacta from Glaxosmithkline by Novartis, we find that these probabilities either declined or mildly increased after the acquisition. Our findings are consistent with the idea that if an entire firm is acquired, its relationships with physicians are more likely to be acquired, but if a single drug is acquired from a firm, these relationships may not be acquired.

2.5 Prescriptions

In this section, we first show that prescriptions are positively correlated with detailing behavior. Then we analyze how prescription patterns change after a drug is acquired. Recall that our prescription data comes from the Medicare Part D Prescriber and

[36] Note, that Crealta had only 604 physicians in its network.

Figure 2.5: β_t^3 from equation 12, along with 95% confidence intervals.



This figure plots β_t^2, and its 95% confidence intervals from equation 12. The X-axis has T_t and the Y-axis has β_t^3.

Table 2.6

			Probability		
Buyer	Target	Drug	Pre	Post	% Diff
actavis	allergan	botox combigan	0.07	0.30	310
arbor	xenoport	horizant	0.15	0.21	36
horizon	crealta	krystexxa	0.44	0.42	-6
glaxosmithkline	novartis	menveo	0.43	0.35	-19
depomed	janssen	nucynta	0.17	0.24	38
otsuka	avanir	nuedexta	0.25	0.30	21
novartis	glaxosmithkline	promacta votrient	0.20	0.23	10
endo	auxilium	xiaflex	0.24	0.23	-5

This table shows the probability that a physician that belongs to the target firm's networks receives a meal for other drugs of the acquiring firm, before and after the acquisition

Drug Public Use Files. Our variable of interest is the total number of 30-day standardized prescription fills, which we observe at the physician-drug-year level. Because our prescription data is at the annual level, we also aggregate our detailing data to the annual level. We construct a variable $Detailed_{pjy}$, which takes a value 1 if a physician p received a meal for drug j in year y, and 0 otherwise. We then merge the annual data on detailing with the annual data on prescriptions and create a balanced panel at the physician-drug-year level. Our full sample contains the drugs that were acquired, and drugs that belong to the same class as the acquired drugs. For each drug, we drop physicians with zero prescriptions for that drug in 2014-2018.

2.5.1 Prescriptions and detailing

In this subsection, we show the positive association between detailing and prescriptions. We use our full sample, which contains the acquired drugs, and other drugs

that belong to the same drug class as the acquired drugs. We use our balanced panel at the physician-drug-year level to estimate the following two regressions:

$$\log(1 + \text{prescriptions})_{pjy} = \beta_0 + \beta_1 \text{Detailed}_{pjy} + \theta_y \times \theta_j + \theta_y \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjy} \quad (13)$$

$$\text{prescribed}_{pjy} = \beta_0 + \beta_1 \text{Detailed}_{pjy} + \theta_y \times \theta_j + \theta_y \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjy} \quad (14)$$

$\log(1 + \text{prescriptions})_{pjy}$ is the number of 30-day standardized prescription fills by physician p for drug j in year y. $\text{prescribed}_{pjy} = 1$ if physician p had positive prescriptions for drug j in year y, and 0 otherwise. $\text{Detailed}_{pjy} = 1$ if physician p received a meal for drug j in year y. In the full specification, we also include drug-year fixed effects, physician-drug fixed effects, and physician-year fixed effects.

Table 2.7 has the results of regressions 13 and 14 in column (4) of Panels A and B respectively. This table shows that when a physician receives detailing for a drug in a year, their prescriptions for this drug go up by 15.8%. When a physician receives detailing for a drug in a year, their probability of prescribing it goes up by 0.03. Columns (1) - (3) have results for the same regression with different combinations of fixed effects. The positive association between detailing and prescriptions holds when we exclude certain fixed effects. Table 2.16 in the Appendix shows the results of this regression when we restrict our analysis to the set of acquired drugs. We continue to see the positive association between detailing and prescriptions in this table.

Table 2.7: Prescriptions and detailing

Panel A	$\log(1 + \text{prescriptions})_{pjy}$ (1)	$\log(1 + \text{prescriptions})_{pjy}$ (2)	$\log(1 + \text{prescriptions})_{pjy}$ (3)	$\log(1 + \text{prescriptions})_{pjy}$ (4)
Detailed	1.208***	1.290***	0.592***	0.158***
	(0.145)	(0.098)	(0.061)	(0.026)
Constant	1.757***	1.747***	1.832***	1.884***
	(0.074)	(0.012)	(0.007)	(0.003)
R^2	0.044	0.137	0.688	0.842
N	3,105,490	3,105,490	3,105,490	3,105,490
Panel B	prescribed_{pjy} (1)	prescribed_{pjy} (2)	prescribed_{pjy} (3)	prescribed_{pjy} (4)
Detailed	0.255***	0.259***	0.104***	0.030***
	(0.029)	(0.018)	(0.010)	(0.007)
Constant	0.504***	0.503***	0.522***	0.531***
	(0.018)	(0.002)	(0.001)	(0.001)
R^2	0.028	0.105	0.647	0.768
N	3,105,490	3,105,490	3,105,490	3,105,490
Drug-Time FE	N	Y	Y	Y
Physician-Drug FE	N	N	N	Y
Physician-Time FE	N	N	Y	Y

SE are clustered at the drug level.

2.5.2 Shift in prescription behavior

In this subsection, we show that there is a shift in the prescription behavior of a drug after it is acquired, which mirrors the shift in physician detailing. Specifically, physicians that belong to the marketing networks of the acquiring firm (i.e. in-network physicians) increase their prescriptions of an acquired drug, after its acquisition. Physicians that belong to the marketing networks of the target firm decrease prescriptions of the acquired drug after its acquisition.

Shift toward the acquiring firm's marketing networks: Our data is a balanced panel at the physician-drug-year level, where for each observation we have information about whether physician p was detailed for drug j in year y, and their total number of prescriptions for drug j in year y. For each acquired drug, we have information

about whether physician p belongs to the marketing networks of its acquiring firm. We use this data to run two sets of regressions. In the first set of equations, we quantify whether among the acquired drugs, prescription behavior changed between the in-network physicians and the out-of-network physicians. We restrict our sample to the set of acquired drugs and estimate equation 15 and 16.

$$\log(1 + \text{prescriptions})_{pjy} = \beta_0 + \sum_{y=-1}^{y=2} \beta_y^1 T_y \times \text{in-network}_{pj} + T_y \times \theta_j + T_y \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjy} \tag{15}$$

$$\text{prescribed}_{pjy} = \beta_0 + \sum_{y=-1}^{y=2} \beta_y^2 T_y \times \text{in-network}_{pj} + \theta_y \times \theta_j + \theta_y \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjy} \tag{16}$$

The dependent variable, $\log(1 + \text{prescriptions})_{pjy}$ in equation 15 is the number of 30-day standardized prescription fills by physician p for drug j in year y. prescribed_{pjy} = 1 if physician p had positive prescriptions for drug j in year y, and 0 otherwise. In-network_{pj} = 1 if physician p received a meal for some other drug belonging to j's acquiring firm, before the acquisition took place, and 0 otherwise. T_y is a set of dummy variables which goes from -1 (one year before the acquisition) to 2 (2 years after the acquisition). 0 is the calendar year in which the acquisition took place. In the full specification, we also include drug-year fixed effects, physician-drug fixed effects, and physician-year fixed effects.

Our coefficients of interest are β_y^1 and β_y^2. The results of this regression are in Table 2.8. We find that one calendar year after a drug is acquired, the difference in prescriptions between in-network physicians and out-of-network increases signifi-

cantly more than this difference one year before the acquisition. The difference in prescriptions between in-network and out-of-network physicians jumps up by 27.4%, one year after the acquisition. Once we account for our full set of fixed effects, the increase in the probability of an in-network physician having positive prescriptions for a drug after it is acquired is positive, but not statistically significant.

In the second set of regressions, we quantify whether prescriptions for a drug by in-network physicians increased after it was acquired, relative to other drugs belonging to the same class. We use the full sample of drugs for this regression, which is the set of acquired drugs, and the set of other drugs belonging to the same class.

We then estimate the following two regressions:

$$\begin{aligned}\log(1+\text{ prescriptions})_{pjy} =&\beta_0 + \sum_{y=-1}^{y=2} \beta_y^3 \text{in-network}_{pj} \times T_y \times \text{acq-drug}_j + \\ &+ \theta_j \times \theta_y + \theta_j \times \theta_p + \theta_y \times \theta_p + \epsilon_{pjy} \end{aligned} \tag{17}$$

$$\begin{aligned}\text{prescribed}_{pjt} =&\beta_0 + \sum_{y=-1}^{y=2} \beta_y^4 \text{in-network}_{pj} \times T_y \times \text{acq-drug}_j + \\ &+ \theta_j \times \theta_y + \theta_j \times \theta_p + \theta_y \times \theta_p + \epsilon_{pjy} \end{aligned} \tag{18}$$

in which acq-drug$_j$ = 1 if the drug was acquired, and 0 if it was not acquired, but belonged to the same class as an acquired drug. In these regressions, our coefficients of interest are β_y^3 and β_y^4. The results from these regressions are in Table 2.9. Again, the base category is T_y = -1, i.e. one year before an acquisition. These results show, that

one and two years after an acquisition, prescriptions for the acquired drug increase among in-network physicians, and this result also holds relative to other drugs of the same class. The total number of prescriptions per in-network physician, as well as the probability of an in-network physician having positive prescriptions for the drug increases, relative to competitor drugs.

Table 2.8: Shift toward acquiring firm's networks

	$\log(1 + \text{prescriptions})_{pjy}$ (1)	$\log(1 + \text{prescriptions})_{pjy}$ (2)	$\log(1 + \text{prescriptions})_{pjy}$ (3)	$\log(1 + \text{prescriptions})_{pjy}$ (4)
$T_t = 0 \times$ in-network	0.074*	0.037	0.214*	0.156
	(0.040)	(0.043)	(0.118)	(0.098)
$T_t = 1 \times$ in-network	0.222***	0.118***	0.337***	0.274***
	(0.040)	(0.043)	(0.122)	(0.101)
$T_t = 2 \times$ in-network	0.174***	0.000	0.322**	0.207*
	(0.040)	(0.043)	(0.132)	(0.114)
Constant	1.602***	1.806***	1.804***	1.826***
	(0.008)	(0.004)	(0.004)	(0.005)
R^2	0.011	0.073	0.938	0.970
N	265,580	265,580	265,580	265,580
	prescribed_{pjy} (1)	prescribed_{pjy} (2)	prescribed_{pjy} (3)	prescribed_{pjy} (4)
$T_t = 0 \times$ in-network	0.024**	0.006	0.038	0.025
	(0.011)	(0.011)	(0.035)	(0.032)
$T_t = 1 \times$ in-network	0.072***	0.028**	0.058	0.044
	(0.011)	(0.011)	(0.036)	(0.033)
$T_t = 2 \times$ in-network	0.064***	–0.007	0.051	0.029
	(0.011)	(0.011)	(0.039)	(0.037)
Constant	0.446***	0.506***	0.507***	0.512***
	(0.002)	(0.001)	(0.001)	(0.002)
R^2	0.011	0.053	0.924	0.953
N	265,580	265,580	265,580	265,580
Drug-Time FE	N	Y	Y	Y
Physician-Drug FE	N	N	N	Y
Physician-Time FE	N	N	Y	Y

SE are clustered at the drug level.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.

Shift away from the target firm's marketing networks: In this subsection, we document that after an acquisition, there is a decline in prescriptions among physicians that belong to the target firms' network. We estimate two sets of regres-

Table 2.9: Shift toward acquiring firm's networks, compared to other drugs belonging to the same class

	$\log(1 + \text{prescriptions})_{pjy}$	$\log(1 + \text{prescriptions})_{pjy}$	$\log(1 + \text{prescriptions})_{pjy}$	$\log(1 + \text{prescriptions})_{pjy}$
	(1)	(2)	(3)	(4)
$T_t = 0 \times$ in-network $\times$ Acq-drug	–0.029	0.050	0.054	0.070*
	(0.042)	(0.043)	(0.045)	(0.041)
$T_t = 1 \times$ in-network $\times$ Acq-drug	0.077*	0.232***	0.198***	0.213***
	(0.042)	(0.043)	(0.045)	(0.041)
$T_t = 2 \times$ in-network $\times$ Acq-drug	0.130***	0.290***	0.358***	0.284***
	(0.042)	(0.043)	(0.045)	(0.042)
Constant	2.150***	1.975***	2.025***	2.053***
	(0.003)	(0.001)	(0.001)	(0.001)
R^2	0.011	0.052	0.642	0.755
N	2,484,392	2,484,392	2,484,392	2,484,392
	prescribed_{pjy}	prescribed_{pjy}	prescribed_{pjy}	prescribed_{pjy}
	(1)	(2)	(3)	(4)
$T_t = 0 \times$ in-network $\times$ Acq-drug	–0.001	0.015	0.024**	0.024**
	(0.011)	(0.011)	(0.012)	(0.011)
$T_t = 1 \times$ in-network $\times$ Acq-drug	0.033***	0.064***	0.057***	0.057***
	(0.011)	(0.011)	(0.012)	(0.011)
$T_t = 2 \times$ in-network $\times$ Acq-drug	0.049***	0.077***	0.086***	0.070***
	(0.011)	(0.011)	(0.012)	(0.011)
Constant	0.599***	0.554***	0.564***	0.568***
	(0.001)	(0.000)	(0.000)	(0.000)
R^2	0.009	0.035	0.632	0.733
N	2,484,392	2,484,392	2,484,392	2,484,392
Drug-Time FE	N	Y	Y	Y
Physician-Drug FE	N	N	N	Y
Physician-Time FE	N	N	Y	Y

SE are clustered at the drug level.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.

sions. In the first set of equations, we quantify whether among the acquired drugs, prescription behavior changed between the target-network physicians and the target-out-of-network physicians. We restrict our sample to the set of acquired drugs and estimate equation 19 and 20.

$$\log(1 + \text{prescriptions})_{pjy} = \beta_0 + \sum_{y=-1}^{y=2} \beta_y^1 T_y \times \text{target-network}_{pj} + \theta_y \times \theta_j + \theta_y \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjy} \tag{19}$$

$$\text{prescribed}_{pjy} = \beta_0 + \sum_{y=-1}^{y=2} \beta_y^2 T_y \times \text{target-network}_{pj} + \theta_y \times \theta_j + \theta_y \times \theta_p + \theta_p \times \theta_j + \epsilon_{pjy} \tag{20}$$

Recall, that target-network physicians are physicians that received detailing for the target firm's drugs prior to the acquisition. The results of these regressions are in Table 2.10. Column 4 of Table 2.10 shows that after an acquisition takes place, physicians that belong to the marketing networks of the target firm have lower prescriptions for the acquired drug, and are less likely to prescribe the acquired drug relative to the the target-out-of-network physicians.

In our second set of regressions, we quantify whether prescriptions for a drug by target-network physicians changed after it was acquired, relative to other drugs belonging to the same class. We use the full sample of drugs for these regressions, which are the set of acquired drugs, and the set of other drugs belonging to the same class.

$$\log(1+\text{ prescriptions})_{pjy} = \beta_0 + \sum_{y=-1}^{y=2} \beta_y^3 \text{target-network}_{pj} \times T_y \times \text{acq-drug}_j + \\ + \theta_j \times \theta_y + \theta_j \times \theta_p + \theta_y \times \theta_p + \epsilon_{pjy} \quad (21)$$

$$\text{prescribed}_{pjt} = \beta_0 + \sum_{y=-1}^{y=2} \beta_y^4 \text{target-network}_{pj} \times T_y \times \text{acq-drug}_j + \\ + \theta_j \times \theta_y + \theta_j \times \theta_p + \theta_y \times \theta_p + \epsilon_{pjy} \quad (22)$$

The results of these regressions are in Table 2.11. This table shows us that relative to other drugs belonging to the same class as an acquired drug, prescriptions, and the probability of a positive prescription for an acquired drug among target-network physicians decline after its acquisition.

2.6 Discussion of results

In this paper, we provide novel evidence on the shift in marketing strategies of pharmaceutical companies firms after they Our results show that: 1) There is a shift in marketing patterns after a drug acquisition takes place. We show that patterns in our data are consistent with firms leveraging their existing relationships with physicians to market a new drug when it's acquired. 2) Physician detailing is correlated with prescription behavior. This result has been established in the literature, and we are able to confirm it for our setting. 3) Prescription behavior changes after a drug acquisition takes place. Physicians that have prior relationships with the acquiring

Table 2.10: Shift away from target firm's networks

	$\log(1 + \text{prescriptions})_{pjy}$	$\log(1 + \text{prescriptions})_{pjy}$	$\log(1 + \text{prescriptions})_{pjy}$	$\log(1 + \text{prescriptions})_{pjy}$
	(1)	(2)	(3)	(4)
$T_t = 0 \times$ target-network	–0.020	0.006	0.040	0.007
	(0.021)	(0.021)	(0.078)	(0.107)
$T_t = 1 \times$ target-network	–0.142*	–0.091**	–0.214	–0.255
	(0.064)	(0.031)	(0.121)	(0.141)
$T_t = 2 \times$ target-network	–0.270**	–0.242***	–0.323	–0.421
	(0.117)	(0.062)	(0.333)	(0.266)
Constant	1.235***	1.516***	1.705***	1.878***
	(0.246)	(0.091)	(0.052)	(0.026)
R^2	0.095	0.158	0.939	0.970
N	265,580	265,580	265,580	265,580
	prescribed_{pjy}	prescribed_{pjy}	prescribed_{pjy}	prescribed_{pjy}
	(1)	(2)	(3)	(4)
$T_t = 0 \times$ target-network	–0.015**	–0.008	–0.005	–0.016
	(0.006)	(0.006)	(0.025)	(0.023)
$T_t = 1 \times$ target-network	–0.058***	–0.043***	–0.080***	–0.092***
	(0.006)	(0.006)	(0.026)	(0.024)
$T_t = 2 \times$ target-network	–0.097***	–0.087***	–0.089***	–0.111***
	(0.006)	(0.006)	(0.027)	(0.026)
Constant	0.371***	0.452***	0.491***	0.527***
	(0.002)	(0.001)	(0.003)	(0.004)
R^2	0.056	0.098	0.924	0.953
N	265,580	265,580	265,580	265,580
Drug-Time FE	N	Y	Y	Y
Physician-Drug FE	N	N	N	Y
Physician-Time FE	N	N	Y	Y

SE are clustered at the drug level.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.

Table 2.11: Shift away from target firm's network, compared to other drugs belonging to the same class

	$\log(1 + \text{prescriptions})_{pjy}$ (1)	$\log(1 + \text{prescriptions})_{pjy}$ (2)	$\log(1 + \text{prescriptions})_{pjy}$ (3)	$\log(1 + \text{prescriptions})_{pjy}$ (4)
$T_t = 0 \times$ target-network $\times$ Acq-drug	–0.179	–0.249*	–0.199*	–0.178**
	(0.157)	(0.119)	(0.096)	(0.069)
$T_t = 1 \times$ target-network $\times$ Acq-drug	–0.354	–0.495*	–0.421	–0.399*
	(0.312)	(0.251)	(0.230)	(0.188)
$T_t = 2 \times$ target-network $\times$ Acq-drug	–0.377	–0.586*	–0.500	–0.490*
	(0.396)	(0.304)	(0.295)	(0.249)
Constant	2.088***	1.896***	2.038***	2.050***
	(0.233)	(0.048)	(0.048)	(0.074)
R^2	0.039	0.079	0.642	0.756
N	2,484,392	2,484,392	2,484,392	2,484,392
	prescribed_{pjy} (1)	prescribed_{pjy} (2)	prescribed_{pjy} (3)	prescribed_{pjy} (4)
$T_t = 0 \times$ target-network $\times$ Acq-drug	–0.058	–0.077**	–0.052*	–0.047*
	(0.043)	(0.034)	(0.023)	(0.022)
$T_t = 1 \times$ target-network $\times$ Acq-drug	–0.118	–0.157*	–0.117**	–0.112**
	(0.086)	(0.073)	(0.048)	(0.041)
$T_t = 2 \times$ target-network $\times$ Acq-drug	–0.133	–0.191*	–0.146**	–0.143**
	(0.110)	(0.090)	(0.064)	(0.056)
Constant	0.592***	0.542***	0.567***	0.567***
	(0.050)	(0.007)	(0.008)	(0.013)
R^2	0.021	0.046	0.633	0.734
N	2,484,392	2,484,392	2,484,392	2,484,392
Drug-Time FE	N	Y	Y	Y
Physician-Drug FE	N	N	N	Y
Physician-Time FE	N	N	Y	Y

SE are clustered at the drug level.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.

firm start prescribing a drug more after it is acquired, and physicians that have prior relationships with target firms prescribe it less. Thus, drug acquisitions have potential implications for consumer (patient welfare), even when they do not have an effect on prices.

Our results have some limitations. First, all the evidence presented in this paper is descriptive. Given that physician-sales representative relationships are very important in this industry, many of these acquisitions may take place with the purpose of giving the acquired drugs access to the marketing networks of the buying firm. Thus, these acquisitions are endogenous. Second, while we hypothesize that the shift in a drug's marketing strategy and prescriptions after it is acquired has the potential to affect patient welfare, we do not quantify this affect. The effect of this shift on patient welfare depends on whether detailing plays an informative or persuasive effect in physician behavior, and whether these shifts cause an increase in the informative or the persuasive component of detailing. We leave the quantification of these welfare effects to future work. Third, our prescription data is restricted to Medicare Part D, and does not capture the universe of prescriptions for each drug.

2.7 Conclusion

The current literature largely analyzes the consumer welfare effects of Mergers & Acquisitions through their effects on prices or product entry and exit. We provide evidence on a new mechanism that could influence consumer (patient) welfare. In industries which have strong marketing networks, accounting for a shift in marketing behavior of firms is important, because it can change consumer welfare by causing a change in demand. We hope that our work helps bridge this gap in the literature.

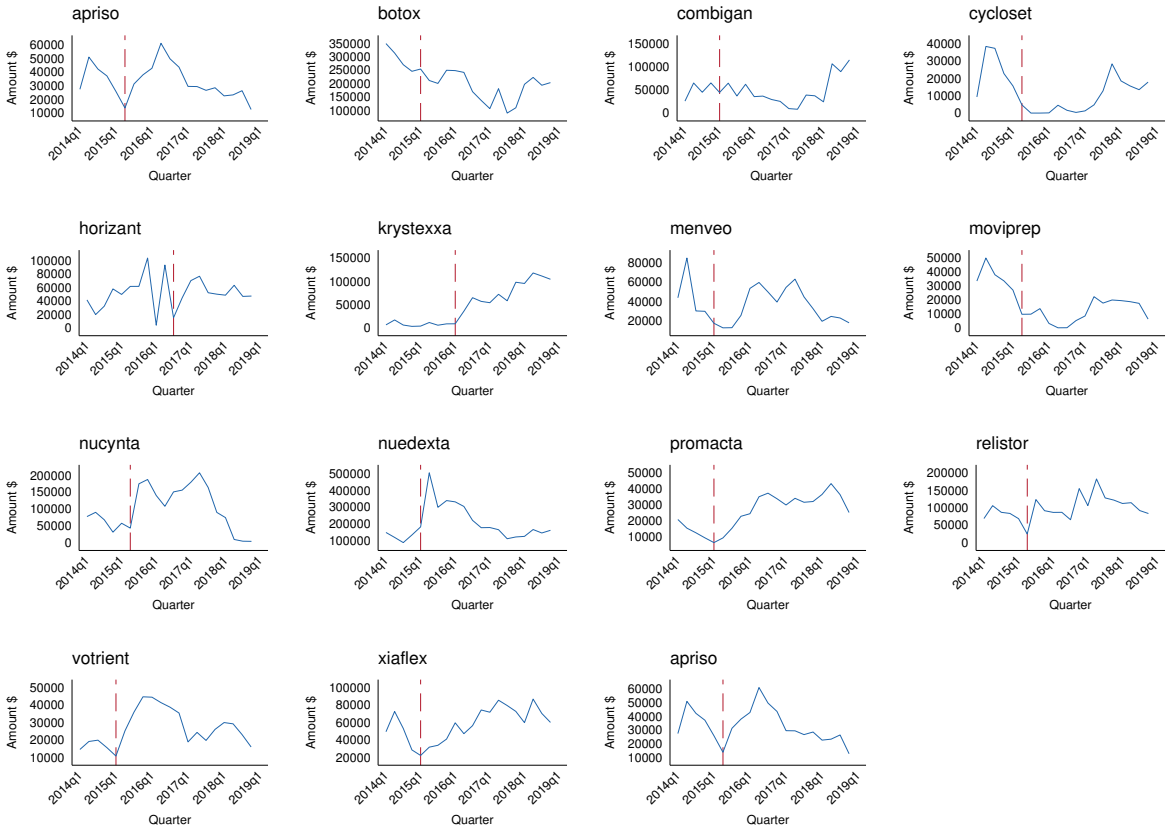
We leave the analysis of the welfare implications of these shifts to future work.

2.8 Appendix

Table 2.12: Target-network physicians

Drug	Number of Physicians	
	Target-network	Target-out-of-network
botox	30,164	6,830
combigan	30,164	1,507
horizant	7,192	49,711
krystexxa	604	21,987
menveo	97,076	25,021
nucynta	106,925	17,029
nuedexta	6,690	11,054
promacta	69,792	1,312
votrient	69,792	5,960
xiaflex	15,502	3,076

Figure 2.6: Trends in marketing payments to physicians



This figure plots total spending on "Food and Drink" payments to physicians over time.

Table 2.13: Results from regression in equation 10

	$Detailed_{pjt}$ (1)	$Detailed_{pjt}$ (2)	$Detailed_{pjt}$ (3)	$Detailed_{pjt}$ (4)
In-network × T_t = -4	–0.009	–0.008	–0.014	–0.010
	(0.010)	(0.010)	(0.018)	(0.018)
In-network × T_t = -3	–0.010	–0.010	–0.009	–0.007
	(0.008)	(0.009)	(0.016)	(0.017)
In-network × T_t = -2	0.006	–0.002	–0.003	–0.001
	(0.006)	(0.009)	(0.013)	(0.012)
In-network × T_t = 0	0.028*	0.030*	0.030**	0.032**
	(0.009)	(0.010)	(0.007)	(0.007)
In-network × T_t = 1	0.033*	0.059*	0.060**	0.062**
	(0.014)	(0.022)	(0.018)	(0.019)
In-network × T_t = 2	0.033*	0.051*	0.053**	0.055**
	(0.013)	(0.017)	(0.015)	(0.016)
In-network × T_t = 3	0.033*	0.047*	0.044*	0.052**
	(0.014)	(0.017)	(0.016)	(0.014)
In-network × T_t = 4	0.036	0.046*	0.044*	0.057*
	(0.016)	(0.017)	(0.019)	(0.018)
In-network × T_t = 5	0.037	0.048*	0.044	0.062*
	(0.016)	(0.018)	(0.022)	(0.020)
In-network × T_t = 6	0.037	0.045*	0.038	0.052*
	(0.017)	(0.017)	(0.022)	(0.018)
In-network × T_t = 7	0.040	0.050*	0.039	0.063**
	(0.021)	(0.020)	(0.026)	(0.018)
In-network × T_t = 8	0.036	0.049*	0.029	0.060**
	(0.023)	(0.021)	(0.018)	(0.017)
R^2	0.011	0.050	0.384	0.596
N	7,449,234	7,449,234	7,449,234	7,449,234
Drug-Time FE	N	Y	Y	Y
Physician-Drug FE	N	N	N	Y
Physician-Time FE	N	N	Y	Y

This table shows the results from the regression in equation 10.
SE are clustered at the drug level.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.

Table 2.14: Results from the regression in equation 11

	$Detailed_{pjt}$ (1)	$Detailed_{pjt}$ (2)	$Detailed_{pjt}$ (3)	$Detailed_{pjt}$ (4)
Target-network $\times$ T_t = -4	0.006	–0.010	–0.026	–0.024
	(0.005)	(0.017)	(0.025)	(0.023)
Target-network $\times$ T_t = -3	0.007	–0.001	–0.002	0.001
	(0.004)	(0.012)	(0.019)	(0.016)
Target-network $\times$ T_t = -2	–0.004	–0.016	–0.023	–0.023
	(0.005)	(0.014)	(0.019)	(0.019)
Target-network $\times$ T_t = 0	–0.025*	–0.054	–0.071	–0.071
	(0.009)	(0.027)	(0.032)	(0.033)
Target-network $\times$ T_t = 1	–0.038*	–0.062*	–0.073*	–0.076*
	(0.014)	(0.024)	(0.024)	(0.028)
Target-network $\times$ T_t = 2	–0.038**	–0.066*	–0.082*	–0.083*
	(0.012)	(0.024)	(0.028)	(0.028)
Target-network $\times$ T_t = 3	–0.038**	–0.065*	–0.096**	–0.090*
	(0.012)	(0.024)	(0.029)	(0.030)
Target-network $\times$ T_t = 4	–0.043*	–0.075*	–0.093**	–0.090*
	(0.013)	(0.024)	(0.024)	(0.029)
Target-network $\times$ T_t = 5	–0.046*	–0.082*	–0.112**	–0.105*
	(0.015)	(0.028)	(0.032)	(0.034)
Target-network $\times$ T_t = 6	–0.044*	–0.081*	–0.110**	–0.105*
	(0.014)	(0.030)	(0.029)	(0.036)
Target-network $\times$ T_t = 7	–0.048**	–0.082*	–0.112**	–0.106*
	(0.014)	(0.032)	(0.033)	(0.040)
Target-network $\times$ T_t = 8	–0.047**	–0.086*	–0.108*	–0.107*
	(0.014)	(0.032)	(0.034)	(0.043)
R^2	0.004	0.064	0.390	0.594
N	7,506,044	7,506,044	7,506,044	7,506,044
Drug-Time FE	N	Y	Y	Y
Physician-Drug FE	N	N	N	Y
Physician-Time FE	N	N	Y	Y

This table shows the results from the regression in equation 11.
SE are clustered at the drug level.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.

Table 2.15: Results from the regression in equation 12

	$Detailed_{pjt}$ (1)	$Detailed_{pjt}$ (2)	$Detailed_{pjt}$ (3)
T_t = -4	0.043	0.043	0.045
	(0.025)	(0.025)	(0.024)
T_t = -3	0.030	0.030	0.017
	(0.013)	(0.013)	(0.011)
T_t = -2	0.020**	0.020**	0.021
	(0.004)	(0.004)	(0.012)
T_t = 0	0.021	0.021	0.001
	(0.028)	(0.028)	(0.018)
T_t = 1	0.071	0.071	–0.001
	(0.052)	(0.052)	(0.024)
T_t = 2	0.087	0.087	–0.018
	(0.053)	(0.053)	(0.018)
T_t = 3	0.076	0.076	–0.054
	(0.054)	(0.054)	(0.029)
T_t = 4	0.066	0.066	–0.036
	(0.054)	(0.054)	(0.039)
T_t = 5	0.095	0.095	0.037
	(0.054)	(0.054)	(0.037)
T_t = 6	0.076	0.076	–0.028
	(0.053)	(0.053)	(0.031)
T_t = 7	0.063	0.063	–0.017
	(0.044)	(0.044)	(0.034)
T_t = 8	0.077	0.077	0.041
	(0.056)	(0.056)	(0.036)
Constant	0.204**	0.204***	0.248***
	(0.061)	(0.032)	(0.015)
R^2	0.004	0.353	0.848
N	2,456,883	2,456,883	2,456,883
Physician-Drug FE	N	N	Y
Physician-Time FE	N	Y	Y

This table shows the results from the regression in equation 12.
SE are clustered at the drug level.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.

Table 2.16: Detailing and prescriptions - acquired drugs only

	$log(1+prescriptions)_{pjy}$ (1)	$log(1+prescriptions)_{pjy}$ (2)	$log(1+prescriptions)_{pjy}$ (3)	$log(1+prescriptions)_{pjy}$ (4)
Detailed	0.678***	1.049***	0.728***	0.320**
	(0.165)	(0.267)	(0.131)	(0.111)
Constant	1.777***	1.726***	1.770***	1.826***
	(0.262)	(0.037)	(0.018)	(0.015)
R^2	0.015	0.104	0.938	0.964
N	331,975	331,975	331,975	331,975
	$prescribed_{pjy}$ (1)	$prescribed_{pjy}$ (2)	$prescribed_{pjy}$ (3)	$prescribed_{pjy}$ (4)
Detailed	0.139***	0.214***	0.135***	0.077***
	(0.024)	(0.031)	(0.027)	(0.020)
Constant	0.503***	0.493***	0.504***	0.512***
	(0.056)	(0.004)	(0.004)	(0.003)
R^2	0.009	0.070	0.922	0.945
N	331,975	331,975	331,975	331,975
Drug-Time FE	N	Y	Y	Y
Physician-Drug FE	N	N	N	Y
Physician-Time FE	N	N	Y	Y

SE are clustered at the drug level.

Figure 2.7: Probability of receiving a detailing payment

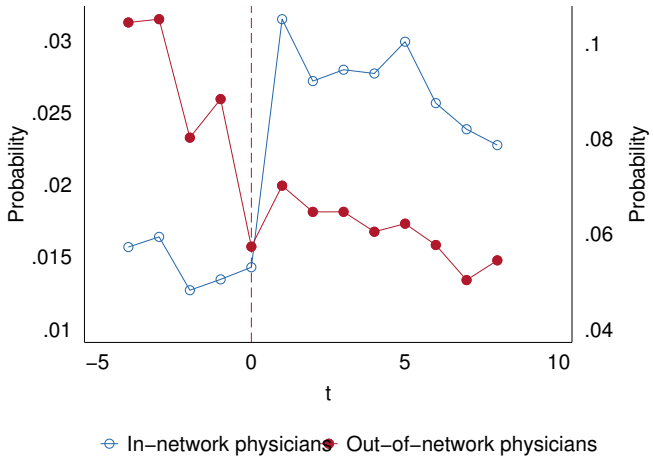


Figure 2.8: Probability of receiving a detailing payment

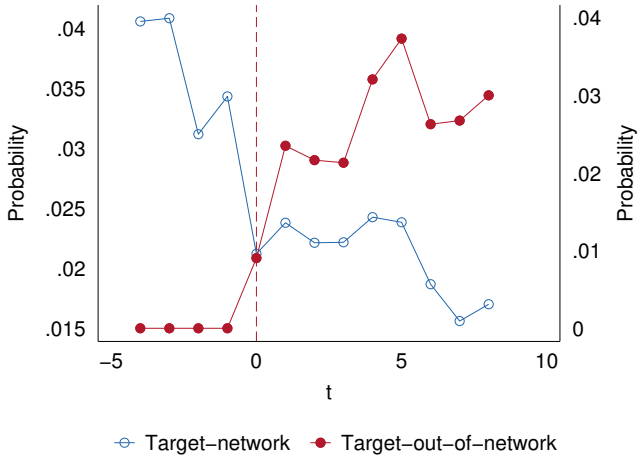


Figure 2.9: Shift away from target firm's marketing networks - robustness

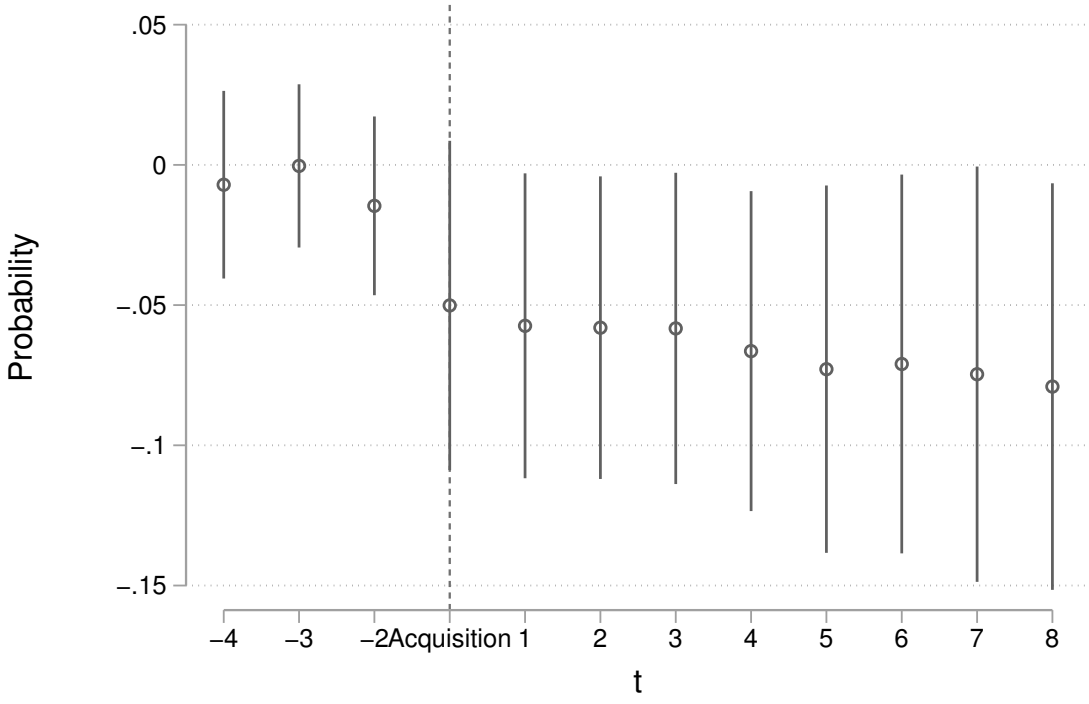


Figure 2.10: Overlap between in-network and target-network physicians

3 Chapter 3: Reputation Shocks and Spillovers: The Case of Implantable Medical Devices

3.1 Introduction

A firm that manufactures products in multiple categories, may have a collective reputation over all these categories (Tirole, 1996). When it faces a negative reputation shock in one category, consumers may take this as a signal of the firm's quality investments across all its categories, and hence there can be demand spillovers to its other categories. The magnitude of these spillovers to other categories can vary between consumers and can depend upon their characteristics. Two characteristics that may affect these magnitudes are 1) exposure to the reputation shock, and 2) their loyalty to the firm. For example, suppose a firm manufactures products in two categories A and B. If the firm has collective reputation over A and B, and it recalls products in category A, we should see a decline in its sales in category B after the recall. Further, say Consumer 1 that bought 100 units in category A from the recalling firm. This consumer was more exposed to the recall than a different Consumer 2 who only bought 1 unit of A from this firm. Hence, we should expect that Consumer 1 responds more strongly to the recall, and we should see larger declines in the future purchases of category B from the recalling firm by Consumer 1, relative to Consumer 2. However, if Consumer 1 also has strong tastes/loyalties for category B manufactured by the recalling firm, or if they have higher costs of switching from the recalling firm, they may respond less strongly to the recall than Consumer 2, who may be loyal to a different firm. Thus, while we expect the magnitude of reputation spillovers to vary between consumers with different exposure to a reputation shock and firm loyalty,

which mechanism dominates is an empirical question.

In this paper, I use the context of Cardiac Rhythm Management (CRM) devices to quantify the effect of a major product recall in one category on the recalling firm's sales in another product category. Two major device categories in CRM are Implantable Cardioverter Defibrillators (ICDs) and Pacemakers. Hospitals buy these devices from manufacturers and implant them in patients. On October 10, 2016, St Jude Medical (SJM) faced a major product recall across almost all its brands of ICDs. This recall was preceded by two deaths and several injuries, and was extensively covered in the news. Pacemakers manufactured by SJM were unaffected by the defects that led to this recall. I quantify the effects of this recall on the aggregate pacemaker sales of SJM and its competitors. I then construct proxies of exposure to the recall and of loyalty toward SJM's pacemakers. I run two sets of regressions: 1) I quantify the variation in hospitals' response to the recall, in terms of pacemaker purchases, based on their loyalty toward SJM's pacemakers, and based on their exposure to the recall. 2) I quantify whether the effect of exposure to the recall varies with loyalty to SJM's pacemakers.

I find that there was aggregate substitution away from SJM's pacemakers, and toward the pacemakers manufactured by its rivals. Specifically, the difference in pacemaker purchases by SJM and its rivals declined by 11% after the recall took place. My measures of exposure to the recall and a hospital's loyalty toward SJM's pacemakers are positively correlated. I find that holding the effect of exposure to the recall constant, hospitals that had lower loyalty toward SJM's pacemakers responded more to the recall. Holding the effect of firm loyalty toward SJM's pacemakers constant, hospitals that have greater exposure to the recall do not respond significantly

differently to it. My findings suggest that firm loyalty played an important role in determining the response to the recalling firm's negative reputation shock, but exposure to a reputation shock did not. Moreover, hospitals that had lower loyalty toward SJM's pacemakers did not have significantly different responses to exposure.

With this paper, I contribute to the literature on seller reputation and collective reputation. Some papers in this genre are Bachmann et al. (2019), Freedman et al. (2012), Cabral and Hortacsu (2010), Barrage et al. (2020), and Bai et al. (2019). Bachmann et al. (2019) finds that after the Volkswagen recalls of 2015, the car sales by other German manufacturers declined. Freedman et al. (2012) finds that after major recalls of toys in China, there were negative spillovers to other manufacturers' toy sales in the same categories, but not to the recalling manufacturers' products in dissimilar categories. Bai et al. (2019) studies the context of recalls in the dairy industry in China, and finds heterogeneous responses by consumers based on their accuracy of information about the recall. In my setting of implantable medical devices, I find that within-firm spillovers dominate. The implantable medical device industry is different from the automobile and toy industries in two aspects: 1) There are regular repeat purchases of implantable medical devices by consumers (hospitals). This creates a continuous variation in exposure to the recall. 2) Firm loyalties, or switching costs between products manufactured by different firms are important in this industry (Pauly and Burns, 2008). This allows me to construct a variable which proxies for firm loyalties, and analyze how firm loyalties affect the response to a recall.

I also contribute to the broader literature that finds that firms' actions have spillovers. For example, Shapiro (2018) studies the context of antidepressants and finds spillovers of a firm's advertising on their rival's demand. Closer to my context,

Grennan et al. (2018) finds that when a new innovation takes place in the medical device industry, it has positive demand spillovers to other categories by the same manufacturer.

Finally, I contribute to the small literature on medical device recalls. Ball et al. (2018) finds that medical device recalls slow innovation for the recalling firms, and increase incremental innovation for competitors. Thirumalai and Sinha (2011) quantifies the sources and the financial consequences of product recalls in the medical device industry. To my knowledge, this paper is the first to study the effects of a medical device recall on the recalling firm's sales.

The rest of this paper is organized as follows: In section 3.2, I describe the CRM industry, the major product recall that took place during the period of my analysis, and my data sources. In section 3.3, I describe my empirical strategy. In section 3.4, I describe my results, and I summarize and discuss them in section 3.5. Finally, I conclude in section 3.6.

3.2 Institutional Setting and Data

3.2.1 Cardiac Rhythm Management Devices

Cardiac Rhythm Management (CRM) devices are implanted in a person's chest and connected via leads to their heart. As the name suggests, they help control a person's cardiac rhythm. Implantable Cardioverter Defibrillators (ICDs) and Pacemakers are two major CRM devices. ICDs deliver a shock to a person's heart when they detect a dangerously abnormal heart rate, and Pacemakers use small electric pulses to keep a person's heart rhythm regular. The batteries in ICDs are supposed to last 5-7 years, and these devices send out an alert, known as an Elective Replacement Indicator

(ERI) alert, about 3 months before their batteries deplete, so that a patient has a 3 month period to get their device replaced. [37]

The industry for CRM devices is concentrated, with more than 95% of CRM device sales in the U.S. coming from 4 manufacturers (Medtronic, St Jude Medical, Boston Scientific, and Biotronik). All the manufacturers produce both ICDs and Pacemakers. Firm loyalties can be important in this industry. For example, physicians may be more familiar with the devices belonging to certain manufacturers due to their training (Pauly and Burns, 2008). Physicians also may have long term relationships with sales representatives, or financial relationships with certain manufacturers (for example consulting relationships) that may create these loyalties.

3.2.2 The Recall

On October 10, 2016, St Jude Medical (SJM) issued a Class I recall of several of their ICDs.[38]. Over 250,000 ICDs were recalled in the U.S. and about 400,000 ICDs were recalled worldwide. The reason for the recall was "premature battery depletion". Specifically, instead of giving patients a three month window for device replacement, the batteries of the recalled ICDs were found to be at a risk of depleting within 24 hours of an ERI alert. Before the recall was announced, two deaths and several injuries had taken place because of this device malfunction. Patients and providers were notified to respond to a replacement alert immediately. Providers were given a list of recommendations to deal with the recall. Specifically, they were told to refrain from implanting any of the recalled devices, respond immediately to an ERI alert

[37] https://www.drugwatch.com/defibrillators/

[38] SKUs belonging to almost all brands were recalled by St Jude Medical. According to the FDA, a Class I recall takes place when "there is a reasonable probability that the use of, or exposure to, a violative product will cause serious adverse health consequences or death"

by replacing the device, and to inform all the patients that had been implanted that their battery may run out earlier than expected.

This recall, and its aftermath was a major shock to SJM. On the day the recall, the stock price of SJM plunged by almost 4% (see Figure 3.1).[39] The left panel of figure 3.2 shows a time series plot of the number of news articles that mention "St Jude Medical ICD", and we see that these mentions shot up the day after the recall, i.e. on October 11, 2016. The right panel of Figure 3.2 shows that there was no such jump for "St Jude Medical Pacemakers" on the same day, as this recall was only for ICDs. Figure 3.3 shows that the recall was a turning point in the market shares of St Jude Medical's ICDs and Pacemakers. The market share for ICDs went up in the quarter that the recall took place, possibly because many ICDs had to be replaced after premature battery depletion. In the long run, market share for the ICDs of SJM was lower than before the recall. In the quarter of the recall, the market share of St Jude Medical's pacemakers plummeted. In the long run, this market share partially recovered but stabilized at a lower level than the pre-recall period.

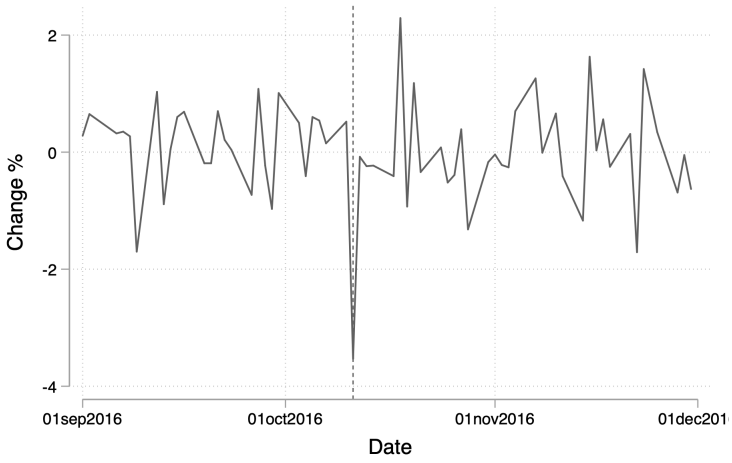
After this recall, in April 2017, the FDA sent a warning letter to St Jude Medical, suggesting that they knew about problems with the ICD batteries for several years before the recall, and continued to sell these ICDs to hospitals (Fornell, 2016). [40]

3.2.3 Data

GlobalData Plc is a market research company that has detailed data on prices and purchase volumes of medical devices. I obtained monthly data on self-reported prices paid and quantities purchased of Implantable Cardioverter Defibrillators (ICDs) and

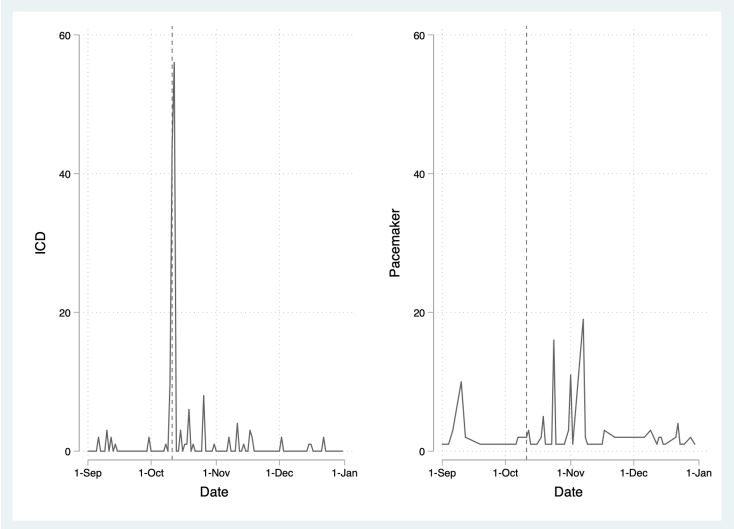
[39]St Jude Medical was acquired by Abbott Laboratories in January, 2017.
[40]St Jude Medical was acquired by Abbott Laboratories in January 2017.

Figure 3.1: Stock price of St Jude Medical



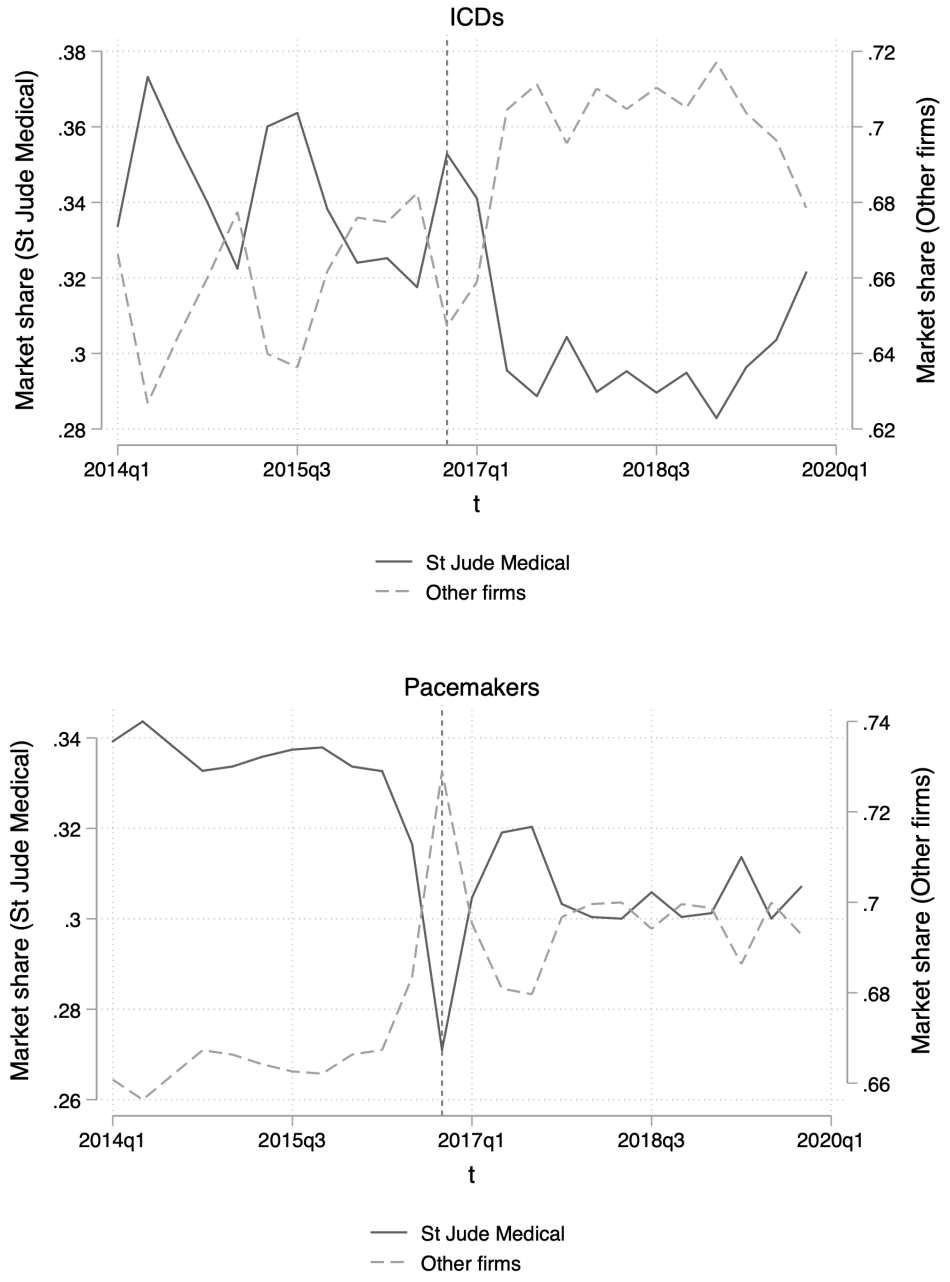
The vertical lines show the day of the recall. The figure on the left shows the time series of the stock price of St Jude Medical. The figure on the right shows the day-to-day percentage change in this stock price.
Source of data: https://www.investing.com/equities/st-jude-medical-historical-data

Figure 3.2: News mentions



Left: News mentions of "St Jude Medical ICD" in September-December 2016.
Right: News mentions of "St Jude Medical Pacemaker" in September-December 2016.
Data source: Newsbank

Figure 3.3: Market shares



This figure shows a time series plot of the market shares for St Jude Medical's ICDs (top) and Pacemakers (bottom), and the market shares for other firms that manufacture ICDs and pacemakers.

Pacemakers at the SKU level, by a sample of healthcare facilities in the US from 2014-2019 from GlobalData. [41] Together, the purchases from these facilities account for about 30% of total sales in the US.

My data has some limitations. First, the healthcare facilities in this database are anonymous, and the only information I have about them are 1) their census region (Midwest, Northeast, South, and West) and 2) their bed size. Second, while I can observe the brand names of each ICD and Pacemaker, the SKUs have been de-identified by GlobalData. I am unable to identify at the brand level the exact ICDs that were recalled. Ideally, it would be interesting to analyze the effects of this reputation shock to SJM on ICDs manufactured by them that were not recalled. However, due to this data limitation, I restrict my analysis of reputation spillovers to Pacemakers.

I aggregate my data to the firm-quarter-hospital-device level. Table 3.6 in the Appendix shows the market shares in my data, by firm and category, in 2014-2019. I drop Boston Scientific from my analysis due to their problem of under-reporting during this period (see footnote 41), and I drop Microport Scientific because they have very low market shares. I then restrict my analysis to hospitals which are in the database in every quarter before the recall took place, i.e. before Q4 2016. My final sample has 418 hospitals; it is an unbalanced panel of hospital level purchases of ICDs and Pacemakers from each firm over 24 quarters (6 years). I restrict my regressions to 4 quarters before the recall and 4 quarters after it. Figure 3.7 in the Appendix shows the distribution of volumes of ICDs and Pacemakers purchased by a hospital in each quarter.

[41] 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

3.3 Empirical Strategy

First, I show that after SJM's ICD recall, there was a decline in the aggregate sales pacemaker sales of St Jude Medical, and an increase in the aggregate pacemaker sales by other firms. Next, I construct proxies for 1) a hospital's exposure to the recall, and 2) a hospital's loyalty to SJM's pacemakers, and show that these declines were larger in hospitals which had lower loyalty to SJM's pacemakers, but exposure to the recall did not affect a hospital's response to it.

3.3.1 Aggregate spillovers

First, I use my data on pacemaker sales to each hospital in a quarter, to run the following two regressions:

$$\log(1 + \text{volume}^{j}_{ht}) = \alpha^1_0 + \beta^1_t T_t + \theta_h + \epsilon_{ht} \tag{23}$$

$$\log(1 + \text{volume}^{o}_{ht}) = \alpha^2_0 + \beta^2_t T_t + \theta_h + \theta_f + \epsilon_{ht} \tag{24}$$

$volume^{j}_{ht}$ is the total volume of pacemakers purchased by hospital h from SJM in quarter t, and $volume^{o}_{ht}$ is the total volume of pacemakers purchased by hospital h from all firms except SJM (the rivals) in quarter t. T_t takes values that go from -4 (4 quarters before the recall) to 4 (4 quarters after the recall). $T_t = 0$ in the quarter of the recall. θ_h captures hospital fixed effects, and θ_f captures firm fixed effects. The base category for this regression is T_t = -1, i.e. one quarter before the recall. Our coefficients of interest are β^1_t and β^2_t. β^1_t tells us whether pacemaker volumes

Scientific, which is why I exclude them from my analysis.

purchased from St Jude Medical changed significantly after the recall, relative to one quarter before the recall. β_t^2 tells us whether pacemaker volumes purchased from the competitors of St Jude Medical changed significantly after the recall, relative to one quarter before the recall.

I then pool the data from all 3 firms together, and run the following regression, restricting my analysis to 4 quarters before the recall and 4 quarters after it:

$$\log(1 + \text{volume}_{fht}) = \alpha^3 + \beta^3 \text{Post}_t \times \text{SJM}_f + \theta_h \times \theta_t + \theta_h \times \theta_f + \epsilon_{fht} \tag{25}$$

$volume_{fht}$ is the volume of pacemakers purchased by hospital h from firm f and time t. $SJM_f = 1$ if the firm the pacemakers are purchased from is St Jude Medical, and 0 otherwise. $\text{Post}_t = 1$ if t$\geq t_{recall}$, where t_{recall} is the quarter of the recall, and 0 otherwise. θ_h captures hospital fixed effects, θ_f captures firm fixed effects, and θ_t captures time fixed effects. In the full specification, I include hospital-time fixed effects to account for hospital-specific trends in purchases of pacemakers, and I include for hospital-firm fixed effects to account for a hospital's average preference for pacemakers from firm f. β^3 tells us, whether the difference between purchase volumes from St Jude Medical and its competitors after the recall is statistically significantly different from this difference before the recall.

3.3.2 Heterogeneity

Different hospitals have 1) Different exposure to the recall, and 2) different firm-specific loyalties toward pacemakers. I use the volume of ICDs that each hospital purchased from St Jude Medical, prior to the recall as a proxy for exposure to the

recall. I proxy for loyalty toward SJM's pacemakers at the hospital level using the fraction of total pacemakers that were purchased from SJM, prior to the recall. I then estimate the heterogeneity in hospitals' responses to the recall depending upon their exposure to the recall, and their loyalty to SJM's pacemakers.

Thus, I define two variables. The first variable is intended to proxy for firm loyalty toward St Jude Medical. It is defined as:

$$\text{loyalty\_SJM}_h = \frac{\sum_{t=-11}^{t=-1} Volume_{ht}\{SJM = 1\}}{\sum_{t=-11}^{t=-1} Volume_{ht}}$$

t = -11 is 11 quarters before the recall (the beginning of my data), and t = -1 is one quarter before the recall. In words, loyalty_SJM$_h$ is the fraction of total pacemakers purchased by hospital h from SJM, in all the quarters before the recall. One might be concerned that if shares of a hospital's pacemaker purchases that come from St Jude Medical in each quarter are very different from each other, we may not be capturing loyalty to St Jude Medical by taking an average over all these quarters. To address this concern, I calculate hospital-level shares of SJM's pacemakers in each quarter before the recall ($share^j_{ht}$), and I run the following regression:

$$share^j_{ht} = \alpha_0 + \beta_t T_t + \theta_h + \epsilon_t$$

where T_t is a set of dummy variables in which t goes from -11 to -1, where -11 is a dummy variable for 11 quarters before the recall and -1 is a dummy variable for 1 quarter before the recall. I use -11 as the base category. β_t from this regression, along with its 95% confidence intervals have been plotted in in Figure 3.8 in the Appendix. This figure confirms that the within-hospital share of pacemaker purchases from SJM

are persistent over time, as β_t does not differ significantly from its value 11 quarters before the recall.

The second variable is intended to proxy for exposure to the recall.[42] I define this variable as:

$$\text{exposure}_h = \log(1 + \sum_{t=-11}^{t=-1} \text{ICD volume}_{ht}\{SJM = 1\})$$

Figure 3.5 in the Appendix shows that there is substantial variation in loyalty toward St Jude Medical's pacemakers, and exposure to the recall between hospitals. From Figure 3.14 in the Appendix, we can see that our measure of firm loyalty is positively correlated with exposure to the recall.

First, I restrict my sample to the pacemaker purchases from SJM, and I estimate the following regression, using data from 4 quarters before the recall until 4 quarters after it:

$$\begin{aligned}\log(1 + \text{volume}^j_{ht}) = \alpha^4_0 + \beta^4_1 \text{post}_t \times (1 \text{ - loyalty\_SJM}_h) \\ + \beta^4_2 \text{post}_t \times \text{exposure}_h + + \theta_h + \theta_t + \epsilon_{ht} \qquad (26)\end{aligned}$$

In this regression, β^4_1 tells us whether, holding the effect of exposure to the recall constant, hospitals that were less loyal to SJM's pacemakers responded differently to the recall. β^4_2 tells us whether holding the effect of loyalty to SJM's pacemakers constant, whether hospitals that were more exposed to the recall responded differently to it.

[42] This proxy is imperfect, as it only goes back to Q1 2014.

In my next regression, I pool data from all firms together, and estimate whether there are heterogeneous responses by hospitals based on exposure and loyalty, relative to other firms:

$$\log(1 + \text{volume}_{fht}) = \alpha_0^5 + \beta_1^5 \text{post}_t \times (1 - \text{loyalty\_SJM}_h) \times SJM_f + \beta_2^5 \text{post}_t \times \text{exposure}_h \times SJM_f + \theta_h \times \theta_t + \theta_h \times \theta_f + \theta_f \times \theta_t + \epsilon_{fht} \quad (27)$$

SJM_f takes a value 1 if the purchase was from SJM, and 0 otherwise. β_1^5 tells us, holding the effect of exposure to the recall constant, whether after the recall, hospitals that had lower loyalty to SJM's pacemakers have a significantly different response to to the recall in terms of pacemaker purchases from SJM, relative to its competitors. β_2^5 tells us, holding the effect of loyalty to SJM's pacemakers constant, whether after the recall, hospitals that had greater exposure to the recall had a significantly different response to it in terms of pacemaker purchases from SJM, relative to its competitors. In the full specification, I account for hospital-time fixed effects, hospital-firm fixed effects, and firm-time fixed effects.

In the next set of regressions, I add an interaction of the effect of exposure with loyalty, to determine whether the response to exposure to the recall changed with loyalty toward SJM's pacemakers.

First, I restrict my sample to the pacemaker purchases from SJM, and I estimate the following regression, using data from 4 quarters before the recall until 4 quarters after it:

$$\log(1 + \text{volume}^j_{ht}) = \alpha^6_0 + \beta^6_1 \text{post}_t \times (1 \text{ - loyalty\_SJM}_h)$$
$$+ \beta^6_2 \text{post}_t \times \text{exposure}_h + \beta^6_3 \text{post}_t \times \text{exposure}_h \times (1 \text{ - loyalty\_SJM}_h)$$
$$+ \theta_h + \theta_t + \epsilon_{ht} \tag{28}$$

β^6_3 tells us whether hospitals that were less loyal to SJM's pacemakers responded differently to greater exposure to the recall.

In my final regression, I include all the firms, and run the following regression:

$$\log(1 + \text{volume}_{fht}) = \alpha^7_0 + \beta^7_1 \text{post}_t \times (1 \text{ - loyalty\_SJM}_h) \times SJM_f$$
$$+ \beta^7_2 \text{post}_t \times \text{exposure}_h \times SJM_f +$$
$$+ \beta^7_3 \text{post}_t \times (1 \text{ - loyalty\_SJM}_h) \times \text{exposure}_h \times SJM_f \tag{29}$$
$$+ \theta_h \times \theta_t + \theta_h \times \theta_f + \theta_f \times \theta_t + \epsilon_{fht} \tag{30}$$

β^5_3 tells us whether hospitals that were less loyal to SJM's pacemakers responded more strongly to greater exposure to the recall in terms of pacemaker purchases from SJM, as compared to its rivals.

3.4 Results

3.4.1 Aggregate spillovers

Figure 3.4 plots β^1_t and β^2_t, from equations 23 and 24, along with their 95% confidence intervals. The top panel shows that in the quarter of the recall, the total volume

of pacemakers purchased from SJM by my sample of hospitals dropped by more than 10%, relative to the quarter before the recall. There was a gradual recovery after this, and by the second quarter after the recall, pacemaker volumes returned to what they were prior to the recall. The bottom panel shows that purchase of pacemakers by the competitors of SJM increased after the recall, relative to one quarter before. This increase is the highest three quarters after the recall. After these three periods, volumes purchased from competitors are still higher than they were before the recall, but to a lesser extent. This evidence is consistent with the gradual aggregate substitution away from SJM's pacemakers after the recall. Table 3.1 shows the results from the regression in equation 25. We see that in the 4 quarters after the recall, the pacemaker volumes purchased by hospitals from SJM were on average 11% lower that they were in the 4 quarters before the recall. In Figure 3.9 the Appendix, I split the pre-recall and post-recall period into different quarters, and I plot the coefficient of interest for each quarter separately, taking one quarter before the recall (-1) as the base category. I show as a robustness check that in each period in the pre-recall period, the difference in the volumes purchased between SJM and competitors was not significantly different from this difference one period before the recall. However, after the recall this difference jumped down, i.e. the volume purchased from SJM declined relative to competitors. In table 3.7 in the appendix, I regress the log of SJM's pacemaker prices on the post recall period, and find that there was no aggregate difference in the prices of pacemakers purchased from SJM before and after the recall.

Table 3.1: Aggregate effects

	log(volume)	log(volume)	log(volume)	log(volume)	log(volume)
	b/se	b/se	b/se	b/se	b/se
Post=1	0.087***	0.000	0.000	0.000	0.000
	(0.033)	(.)	(.)	(.)	(.)
Post=1 × SJM=1	–0.137***	–0.147***	–0.129***	–0.129***	–0.110**
	(0.050)	(0.049)	(0.049)	(0.048)	(0.047)
Constant	1.886***	1.965***	1.961***	1.961***	1.957***
	(0.045)	(0.011)	(0.011)	(0.010)	(0.010)
R^2	0.001	0.333	0.465	0.517	0.646
N	8,708	8,708	8,708	8,708	8,708
Hospital FE	N	Y	N	N	N
Time FE	N	Y	N	Y	N
Firm FE	N	Y	Y	N	N
Hospital-Time FE	N	N	Y	N	Y
Hospital-Firm FE	N	N	N	Y	Y

This table shows the results from the regression in equation 25.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the hospital level.

3.4.2 Heterogeneity

So far I have shown that even though there was no recall for SJM's pacemakers, there was significant decline in their purchases after the recall. In this section, I attempt to quantify how these declines vary by heterogeneity in loyalty toward SJM's pacemakers, and exposure to the recalls.

Table 3.2 shows that β_1^4 is negative, i.e. in the post recall period, holding the effect of exposure to the recall constant, hospitals that were less loyal to SJM's pacemakers reduced their pacemaker purchases from SJM more. After we account for hospital and time fixed effects, the magnitude of this coefficient is -0.68. The average value of (1 - loyalty_SJM$_h$) is 0.69. Thus, holding exposure to the recall constant, a hospital that has average loyalty to SJM's pacemakers reduces their pacemaker purchases from SJM by 47%. Another way to interpret this regression is that as the share of pacemakers purchased from SJM by hospitals before the recall decreases by an additional 0.10, the volume of pacemakers purchased from SJM after the recall declines by 6.8%. Table 3.2 also shows that holding the effect of loyalty constant, there was no heterogeneous spillover effect based on exposure to the recall. Table 3.8 in the Appendix shows that post recall prices were lower for hospitals that were more exposed to the recall, but they did not change for hospitals that were less loyal to SJM's pacemakers. This is confirmed in Figure 3.10, which splits the $post_t$ variable into different quarters, uses one quarter before the recall as the base period, and shows that there was no pre-trend in prices before the recall, but after the recall hospitals that were more exposed to it experienced declines in SJM's pacemaker prices.

The results of equation 27 are in Table 3.3. This table confirms that we are not just picking up a general trend in pacemaker purchases in the results of the regression

in equation 26. Specifically, holding exposure to the recall constant, after the recall took place, hospitals that had lower loyalty toward SJM's pacemakers had greater substitution away from their pacemakers after the recall, as compared to SJM's competitors. The coefficient is higher in absolute terms, suggesting that hospitals with less loyalty toward SJM's pacemakers started substituting away from SJM's pacemakers and toward those of SJM's rivals disproportionately more after the recall. Again, there was no significant effect of exposure on spillovers relative to other firms. Figures 3.11 and 3.13 in the appendix split the the data into different quarters, use one quarter before the recall as a base period, and plot how the coefficients of interest (β_1^4, β_1^5, and β_2^4, β_2^5) change over time as a robustness check. These figures show that there was no pre-trend in the responsiveness of volumes purchased by a hospital from SJM to loyalty and exposure.

Finally, in equations 28 and 29 I interact my proxy for exposure to the recall with my proxy for loyalty to SJM's pacemakers. When I restrict my analysis to St Jude Medical, I find that as loyalty to SJM's pacemakers changes, there is no significant difference in the way a hospital responds to exposure (Table 3.4). This is also true relative to competitors, i.e. when I include other firms in my analysis. (Table 3.5). Figure 3.12 in the appendix confirms that this result is not driven by noise.

3.5 Summary and Discussion

In this paper, I find that after SJM faced a major ICD product recall, there were spillovers on the the sales for its other, closely related products that were unaffected by the recall. I show evidence that after the ICD recall, hospitals (consumers) substituted away from SJM's pacemakers and toward the pacemakers of their competitors. I also

Table 3.2: Loyalty and exposure

	log(volume)	log(volume)	log(volume)
	b/se	b/se	b/se
Exposure	0.413***	0.413***	0.000
	(0.026)	(0.026)	(.)
Post=1	0.448***	0.000	0.000
	(0.170)	(.)	(.)
Post=1 × Exposure	–0.001	–0.001	0.027
	(0.024)	(0.024)	(0.023)
(1 − Loyalty_SJM)	–0.792***	–0.792***	0.000
	(0.196)	(0.196)	(.)
Post=1 × (1 − Loyalty_SJM)	–0.713***	–0.712***	–0.684***
	(0.165)	(0.165)	(0.159)
Constant	0.962***	1.223***	2.140***
	(0.186)	(0.162)	(0.094)
R^2	0.472	0.475	0.735
N	3,209	3,209	3,209
Hospital FE	N	N	Y
Time FE	N	Y	Y

This table shows the results from the regression in equation 26.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the hospital level.

Table 3.3: Loyalty and exposure, relative to other firms

	log(volume)	log(volume)	log(volume)	log(volume)	log(volume)
	b/se	b/se	b/se	b/se	b/se
Exposure	0.246***	0.000	0.296***	0.000	0.000
	(0.025)	(.)	(0.027)	(.)	(.)
Post=1	–0.530***	0.000	0.000	0.000	0.000
	(0.143)	(.)	(.)	(.)	(.)
Post=1 × Exposure	0.047**	0.060***	0.052**	0.000	0.000
	(0.021)	(0.019)	(0.021)	(.)	(.)
SJM=1	1.101***	0.000	0.000	0.000	0.000
	(0.195)	(.)	(.)	(.)	(.)
SJM=1 × Exposure	0.167***	0.135***	0.117***	0.131***	0.000
	(0.028)	(0.027)	(0.028)	(0.027)	(.)
Post=1 × SJM=1	0.977***	1.008***	0.000	0.000	0.000
	(0.184)	(0.190)	(.)	(.)	(.)
Post=1 × SJM=1 × Exposure	–0.048*	–0.048*	–0.052**	–0.041	–0.007
	(0.026)	(0.027)	(0.026)	(0.027)	(0.027)
(1 − Loyalty_SJM)	1.603***	0.000	1.717***	0.000	0.000
	(0.170)	(.)	(0.175)	(.)	(.)
Post=1 × (1 − Loyalty_SJM)	0.641***	0.709***	0.732***	0.000	0.000
	(0.135)	(0.123)	(0.127)	(.)	(.)
SJM=1 × (1 − Loyalty_SJM)	–2.395***	–2.641***	–2.509***	–2.706***	0.000
	(0.207)	(0.187)	(0.196)	(0.189)	(.)
Post=1 × SJM=1 × (1 − Loyalty_SJM)	–1.355***	–1.381***	–1.443***	–1.333***	–1.304***
	(0.183)	(0.180)	(0.177)	(0.175)	(0.169)
Constant	–0.139	2.013***	–0.026	2.652***	2.128***
	(0.175)	(0.119)	(0.141)	(0.051)	(0.038)
R^2	0.260	0.577	0.399	0.705	0.886
N	8,703	8,703	8,703	8,703	8,703
Hospital FE	N	Y	N	N	N
Time FE	N	Y	N	N	N
Firm FE	N	Y	N	N	N
Hospital-Time FE	N	N	N	Y	Y
Hospital-Firm FE	N	N	N	N	Y
Firm-Time FE	N	N	Y	Y	Y

This table shows the results from the regression in equation 27.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the hospital level.

Table 3.4: Interaction between loyalty and exposure

	log(volume)	log(volume)	log(volume)
	b/se	b/se	b/se
Exposure	0.318***	0.318***	0.000
	(0.088)	(0.088)	(.)
Post=1	0.455	0.000	0.000
	(0.322)	(.)	(.)
Post=1 × Exposure	–0.003	–0.002	0.051
	(0.074)	(0.074)	(0.076)
(1 − Loyalty_SJM)	–1.301***	–1.301***	0.000
	(0.411)	(0.412)	(.)
Exposure × (1 − Loyalty_SJM)	0.139	0.139	0.000
	(0.116)	(0.116)	(.)
Post=1 × (1 − Loyalty_SJM)	–0.731*	–0.726*	–0.550
	(0.388)	(0.388)	(0.418)
Post=1 × Exposure × (1 − Loyalty_SJM)	0.004	0.003	–0.036
	(0.094)	(0.095)	(0.097)
Constant	1.329***	1.592***	2.085***
	(0.335)	(0.305)	(0.197)
R^2	0.475	0.477	0.735
N	3,209	3,209	3,209
Hospital FE	N	N	Y
Time FE	N	Y	Y

This table shows the results from the regression in equation 28.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the hospital level.

Table 3.5: Interaction between loyalty and exposure, relative to other firms

	log(volume)	log(volume)	log(volume)	log(volume)	log(volume)
	b/se	b/se	b/se	b/se	b/se
Exposure	0.268***	0.000	0.241***	0.000	0.000
	(0.080)	(.)	(0.086)	(.)	(.)
Post=1	–0.187	0.000	0.000	0.000	0.000
	(0.263)	(.)	(.)	(.)	(.)
Post=1 × Exposure	–0.038	–0.005	–0.003	0.000	0.000
	(0.057)	(0.045)	(0.050)	(.)	(.)
SJM=1	1.557***	0.000	0.000	0.000	0.000
	(0.381)	(.)	(.)	(.)	(.)
SJM=1 × Exposure	0.050	0.080	0.077	0.062	0.000
	(0.094)	(0.086)	(0.091)	(0.087)	(.)
Post=1 × SJM=1	0.642*	0.608	0.000	0.000	0.000
	(0.336)	(0.377)	(.)	(.)	(.)
Post=1 × SJM=1 × Exposure	0.036	0.052	0.002	0.074	0.103
	(0.072)	(0.080)	(0.072)	(0.070)	(0.073)
(1 − Loyalty_SJM)	1.719***	0.000	1.435***	0.000	0.000
	(0.456)	(.)	(0.474)	(.)	(.)
Exposure × (1 − Loyalty_SJM)	–0.030	0.000	0.075	0.000	0.000
	(0.106)	(.)	(0.108)	(.)	(.)
Post=1 × (1 − Loyalty_SJM)	0.204	0.377	0.452	0.000	0.000
	(0.312)	(0.246)	(0.281)	(.)	(.)
Post=1 × Exposure × (1 − Loyalty_SJM)	0.115	0.087	0.074	0.000	0.000
	(0.073)	(0.063)	(0.068)	(.)	(.)
SJM=1 × (1 − Loyalty_SJM)	–3.020***	–2.926***	–2.736***	–3.082***	0.000
	(0.485)	(0.462)	(0.478)	(0.479)	(.)
SJM=1 × Exposure × (1 − Loyalty_SJM)	0.169	0.076	0.064	0.098	0.000
	(0.127)	(0.116)	(0.121)	(0.119)	(.)
Post=1 × SJM=1 × (1 − Loyalty_SJM)	–0.935**	–0.852*	–1.178***	–0.699	–0.690
	(0.423)	(0.472)	(0.426)	(0.438)	(0.451)
Post=1 × SJM=1 × Exposure × (1 − Loyalty_SJM)	–0.111	–0.140	–0.070	–0.166*	–0.156
	(0.097)	(0.106)	(0.097)	(0.098)	(0.098)
Constant	–0.229	2.244***	0.329	2.654***	2.032***
	(0.366)	(0.202)	(0.281)	(0.116)	(0.075)
R^2	0.261	0.577	0.401	0.705	0.887
N	8,703	8,703	8,703	8,703	8,703
Hospital FE	N	Y	N	N	N
Time FE	N	Y	N	N	N
Firm FE	N	Y	N	N	N
Hospital-Time FE	N	N	N	Y	Y
Hospital-Firm FE	N	N	N	N	Y
Firm-Time FE	N	N	Y	Y	Y

This table shows the results from the regression in equation 29.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the hospital level.

show evidence that this substitution is driven by hospitals that were buying fewer pacemakers as a fraction of their total pacemaker purchases from SJM, before the recall. I also find that on average, exposure to the recall did not play a role in determining the spillover effects. Moreover, the effect of exposure did not vary with loyalty toward SJM's pacemakers.

My results highlight that a firm can have collective reputation across its different product categories. When it faces a reputation shock in one category, it suffers losses in other categories. The magnitude of these losses, however, depend upon the fraction of purchases of each consumer in these other categories that came from this firm, prior to the reputation shock. This is consistent with the idea that consumers with high brand loyalties/switching costs respond less to a reputation shock.

This paper has some limitations. First, the SKUs in my product data are de-identified. I cannot map the recalled SKUs to the SKUs in my data. Thus, I am unable to quantify spillovers from the recall to other ICDs manufactured by SJM that were not recalled. Second, while I find that hospitals substituted away from SJM's pacemakers and toward the pacemakers of their rivals, it is possible that there were spillover effects on the entire CRM industry, i.e. total pacemakers. Figure 3.6 shows that aggregate pacemaker sales increased steadily during this period, which suggests that negative spillovers to other pacemaker manufacturers were not substantial. Third, I proxy for exposure to the recall using the number of ICDs purchased by a hospital from SJM in January 2014-September 2016. However, the recalled ICDs were being sold before 2014 as well. If a hospital did not buy a large volume of ICDs from SJM in January 2014-September 2016, but purchased a large volume before that, they would be assumed to have low exposure to the recall, even though they

would have been highly exposed to it in reality. Fourth, pacemakers and ICDs are different categories of products, but they are both related, as they are CRM devices. It would be interesting to quantify spillovers to other product categories outside the CRM realm. Finally, my analysis is based on one major recall. Recalls among CRM devices are very common, and a vast majority of them are minor. The example in this paper is of a particularly large recall, and we should be wary of generalizing these results to all recalls in this industry.

3.6 Conclusion

I find that firms have collective reputation across their product categories. Thus, firms that manufacture products in multiple categories may face greater consequences of a major reputation shock to one category. Firm loyalties are important in determining the extent of these consequences. My results suggest that consumers that can switch more easily to other alternatives have a stronger response to a reputation shock.

3.7 Appendix

Table 3.6: Shares

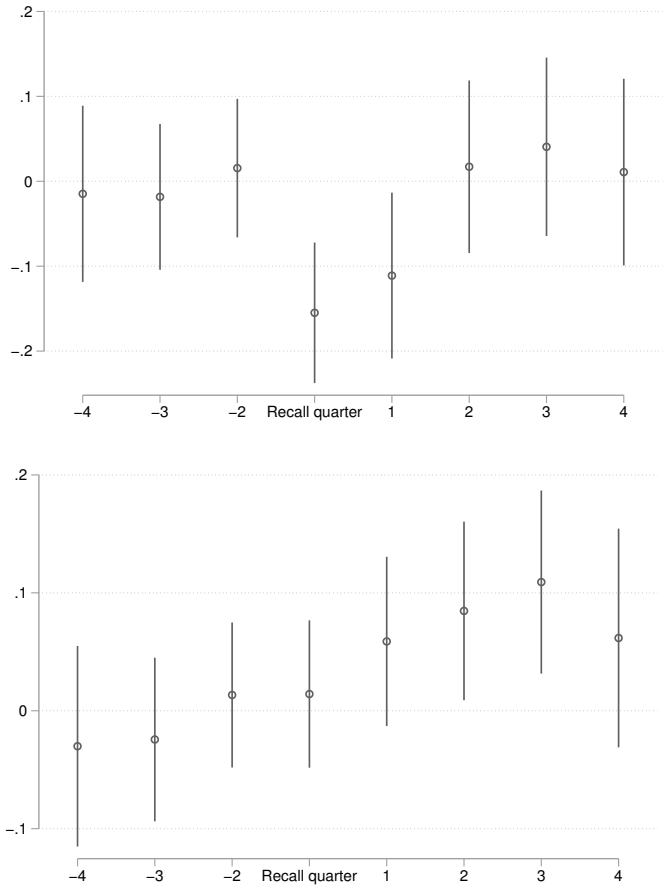
Firm	Pacemaker	ICD
Biotronik	0.09	0.08
Boston Scientific Corp	0.05	0.05
Medtronic Plc	0.54	0.54
Microport Scientific Corp	0.00	0.00
St Jude Medical	0.32	0.32

Table 3.7: Aggregate effects - prices

	log(prices)	log(prices)
	b/se	b/se
post=1	–0.011	–0.002
	(0.010)	(0.010)
Constant	8.339***	8.334***
	(0.014)	(0.006)
R^2	0.000	0.646
N	2,707	2,707
Hospital FE	N	Y

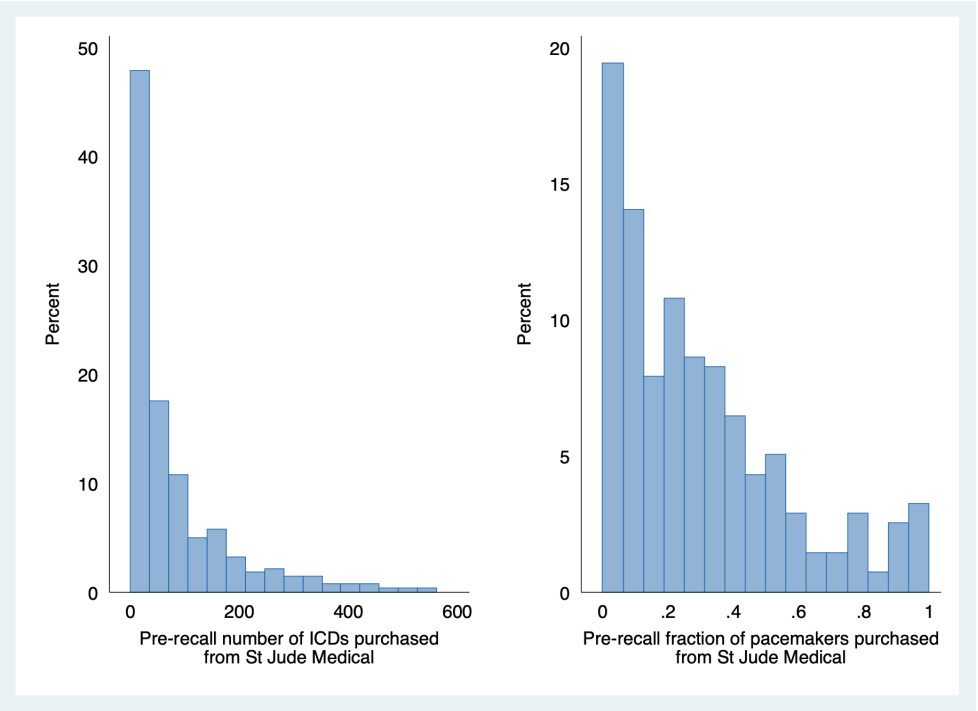
This table regresses average pacemaker prices in a hospital on the post recall period.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the hospital level.

Figure 3.4: Aggregate effects



This top panel plots β_t^1 from equation 23, along with its 95% confidence interval. The bottom panel plots β_t^2 from equation 24, along with its 95% confidence interval.

Figure 3.5: Variation in exposure and loyalty



The left figure shows the distribution of the number of ICDs purchased by a hospital before the recall took place. The right figure shows the fraction of total Pacemaker purchases in a hospital that come from St Jude Medical, before the recall.

Figure 3.6: Pacemaker volumes

This figure shows the aggregate number of pacemakers sales across all hospitals.

Figure 3.7: Distribution of volume purchased in a hospital-quarter

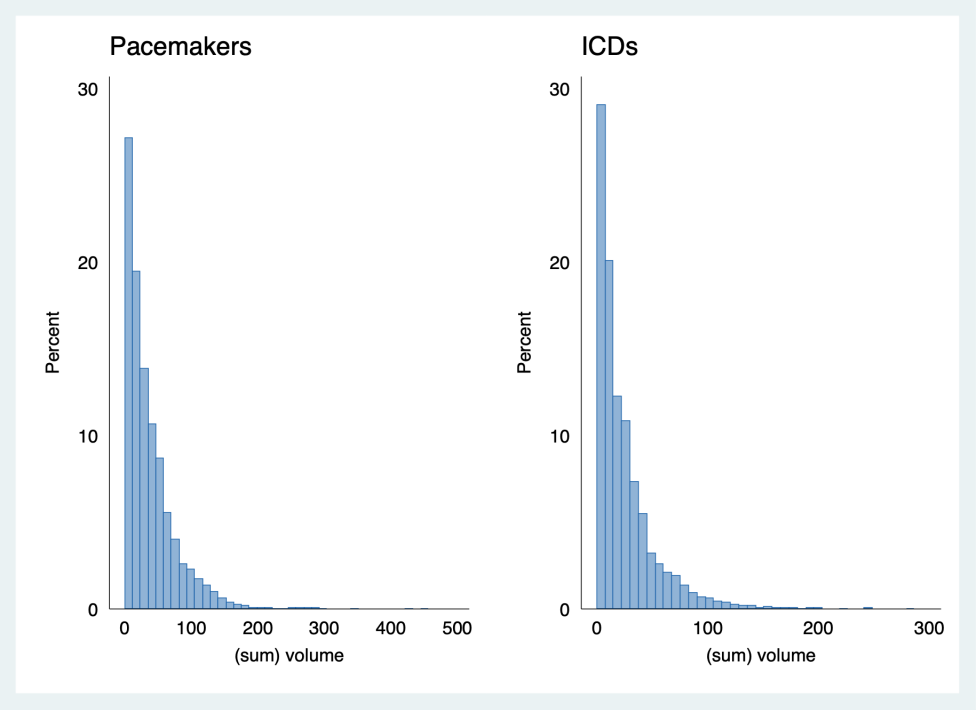


Figure 3.8: Loyalty proxy - Robustness check

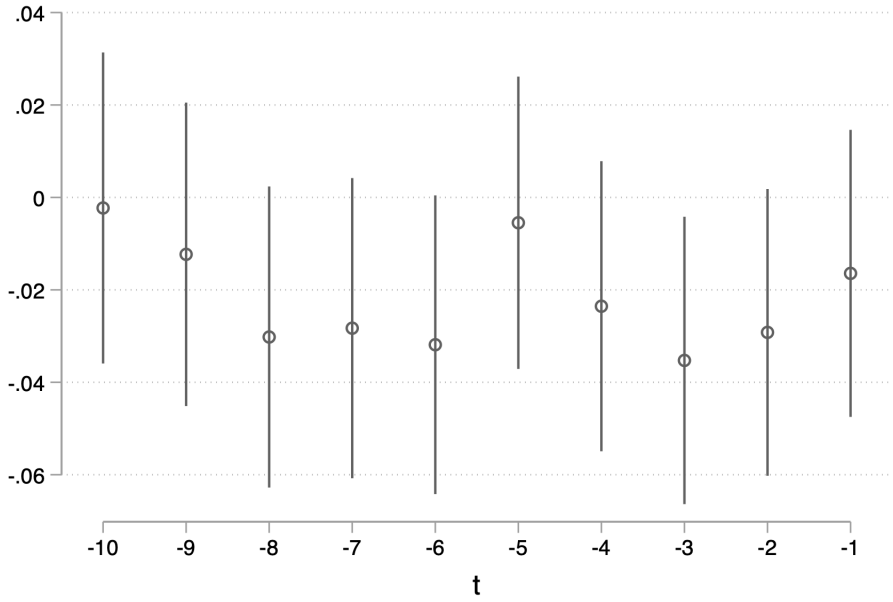
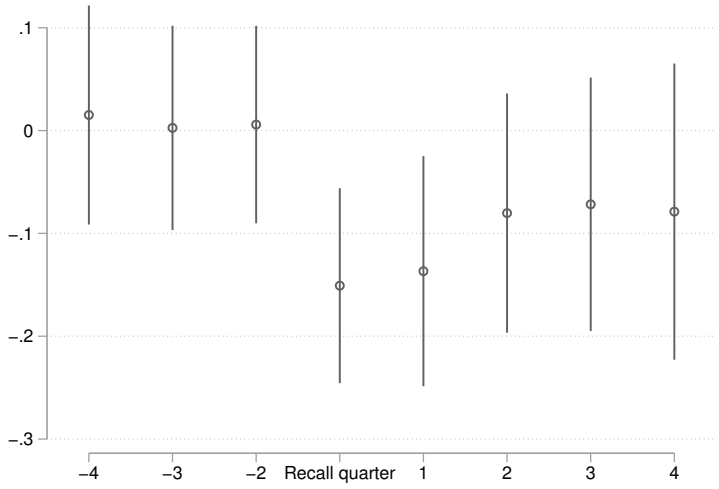
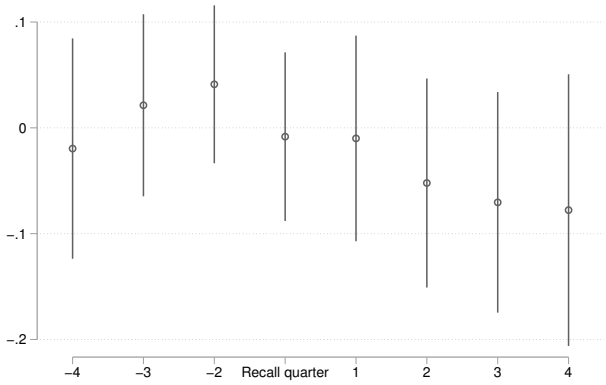


Figure 3.9: Aggregate effects

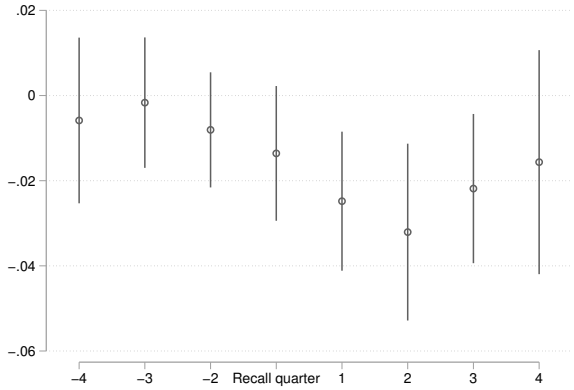


This figure splits $post_t$ from equation 25 into separate quarters t, and plots β_t^3, with t = -1, or one quarter before the recall being the reference period.

Figure 3.10: Heterogeneity in prices based on firm loyalties toward SJM's pacemakers, and exposure to the recall

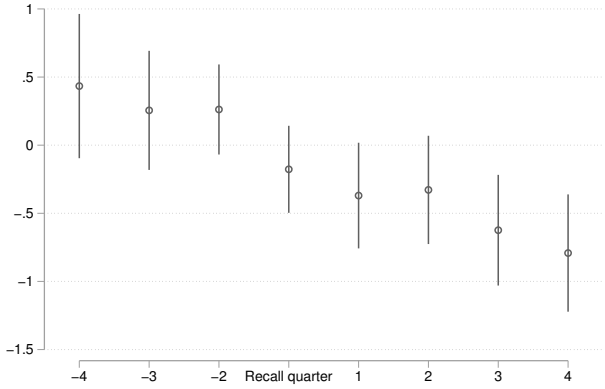


(a) This figure shows whether SJM's pacemaker prices more loyal hospitals are significantly different from these prices one quarter before the recall

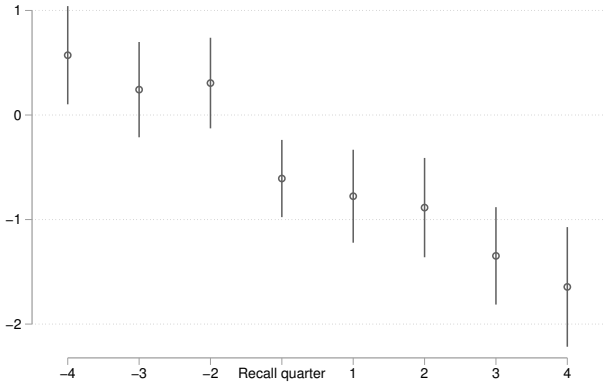


(b) This figure shows whether SJM's pacemaker prices more loyal hospitals are significantly different from these prices one quarter before the recall

Figure 3.11: Heterogeneity based on firm loyalties toward pacemakers



(a) This figure splits $post_t$ from equation 26 into separate quarters t, and plots β^4_{1t}, with t = -1, or one quarter before the recall being the reference period.



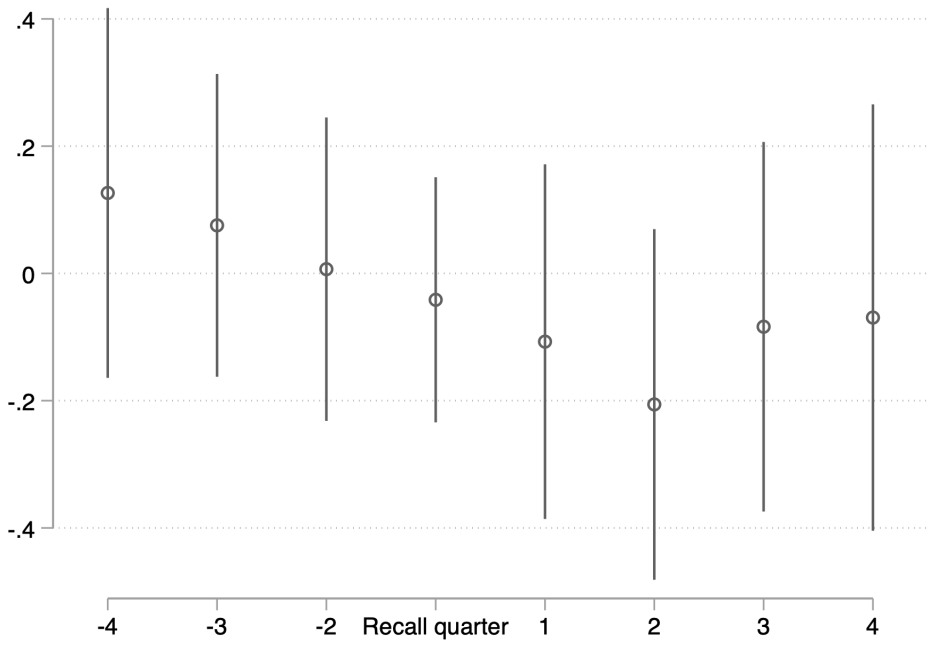
(b) This figure splits $post_t$ from equation 27 into separate quarters t, and plots β^5_{1t}, with t = -1, or one quarter before the recall being the reference period.

Table 3.8: Loyalty and exposure - prices

	log(prices)	log(prices)	log(prices)
	b/se	b/se	b/se
Exposure	0.030***	0.029***	0.000
	(0.009)	(0.009)	(.)
post=1	0.060	0.000	0.000
	(0.040)	(.)	(.)
post=1 × Exposure	–0.007	–0.007	–0.018***
	(0.007)	(0.007)	(0.006)
(1 − Loyalty_SJM)	0.162***	0.162***	0.000
	(0.049)	(0.049)	(.)
post=1 × (1 − Loyalty_SJM)	–0.065*	–0.067*	–0.056*
	(0.037)	(0.037)	(0.034)
Constant	8.118***	8.154***	8.395***
	(0.055)	(0.044)	(0.020)
R^2	0.028	0.035	0.652
N	2,706	2,706	2,706
Hospital FE	N	N	Y
Time FE	N	Y	Y

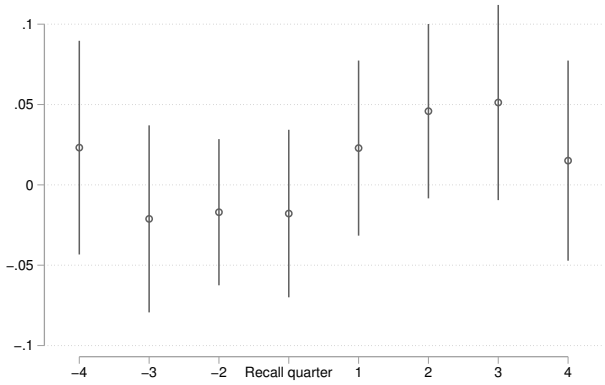
This table regresses average pacemaker prices in a hospital on the post recall period.
Standard errors in parentheses. p<0.10, ** p<0.05, *** p<0.01.
Standard errors are clustered at the hospital level.

Figure 3.12: Heterogeneity based on exposure and loyalty

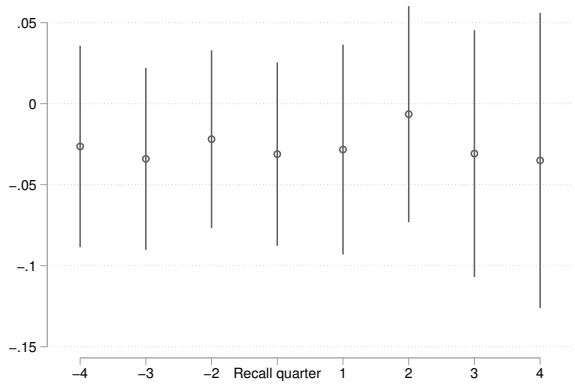


This figure splits $post_t$ from equation 27 into separate quarters t, and plots β_{3t}^{7}, with t = -1, or one quarter before the recall being the reference period.

Figure 3.13: Heterogeneity based on exposure to the recall

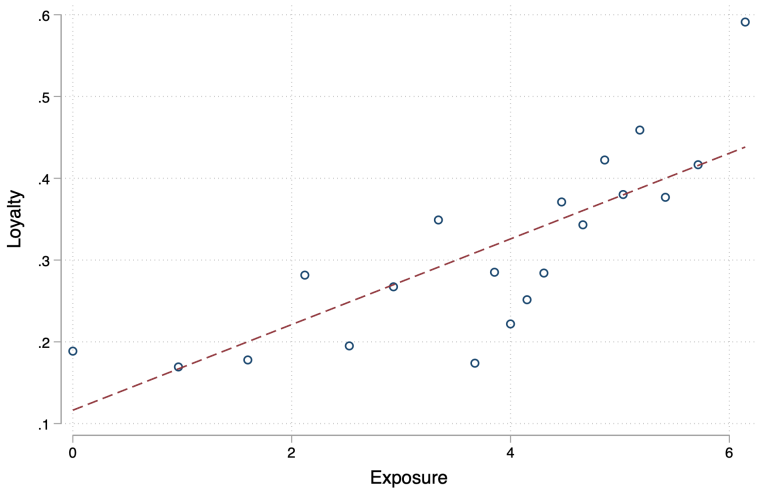


(a) This figure splits $post_t$ from equation 26 into separate quarters t, and plots β^4_{2t}, with t = -1, or one quarter before the recall being the reference period.



(b) This figure splits $post_t$ from equation 27 into separate quarters t, and plots β^5_{2t}, with t = -1, or one quarter before the recall being the reference period.

Figure 3.14: Correlation between exposure to the recall, and firm loyalty toward pacemakers



This figure shows a bin scatter plot of my proxies of loyalty against exposure.

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