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The Effect of Price Caps on Advertising to Physicians: Evidence from the 340b Drug Pricing Program

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ABSTRACT

We study the effect of price caps on the provision of costly effort by pharmaceutical firms using variation in drug discounts generated by a price regulation program that allows eligible hospitals to purchase outpatient drugs at steep discounts. These discounts directly affect drug manufacturers' markups, and may change firms' incentives to exert promotional effort targeted towards physicians at these hospitals. We find that the effects of price regulation on pharmaceutical firm effort depend crucially on the design of the regulations. Using detailed data on marketing payments from pharmaceutical firms to physicians, we observe that physicians receive 13% fewer promotional payments after their hospitals take up the program. The design of the price caps imply that discounts tend to increase with a drug's age. Consistent with theoretical predictions, we find that pharmaceutical firms shift promotional payments away from older drugs and towards newer drugs, which are less affected by the price caps. Understanding these strategic, non-price adjustments is important for policymakers seeking to design effective regulations targeting specific products.

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1 Introduction

Regulatory pricing restrictions may prompt firms to respond strategically in non-price aspects of their supply decisions, such as promotional effort. Despite the potential significance of these unintended consequences, the ability of policymakers to study such responses is often constrained by the fact that they observe only joint decisions across strategic variables in equilibrium. We leverage exogenous price variation driven by government-mandated price caps on prescription drug purchases by certain hospitals to analyze pharmaceutical firms' marginal incentives to promote their drugs.

The promotional outreach we analyze is in-kind payments to physicians. Pharmaceutical firms often purchase meals for physicians in order to create an opportunity to present information about drugs. These in-kind payments are an economically important feature of prescription drug markets: in 2023, pharmaceutical firms spent over $12 billion on in-kind transfers to physicians (Centers for Medicare and Medicaid Services). Prior research has shown that physician payments and other forms of detailing influence prescription drug utilization, spending, and health outcomes (e.g., Ching and Ishihara (2012); Chintagunta et al. (2012); Grennan et al. (2021)). Using granular data on these payments, we study both the average response of promotional effort to price regulation and how this response varies across drugs.[1]

Our empirical analysis leverages price variation generated by the 340b Drug Pricing Program. The 340b program imposes price caps on drugs purchased by participating hospitals, allowing them to acquire drugs at steep discounts.[2] Pharmaceutical firms are not compensated by the government for revenues lost to the price caps mandated by the 340b program. The 340b program offers a unique setting that allows us to isolate the effect of changes in markups on the marginal promotional incentives of pharmaceutical firms. First, the discounts granted to 340b hospitals are large: hospitals reportedly enjoyed average discounts of 47% off list prices, but these discounts can grow as large as 99% (Fein (2020)). Second, the design of the 340b program's pricing formula causes discounts to differ across drugs, which in turn should lead to heterogeneous responses by firms across drugs. Third, because other strategic variables chosen by pharmaceutical firms, such as drug prices and direct-to-consumer advertising, are typically determined nationally, promotional effort targeted to physicians stands out as one of the few localized and flexible margins of adjustment available to firms in response to geographically-dispersed hospitals joining the 340b program.

A common presumption in drug policy debates is that pharmaceutical manufacturers will reduce effort in response to a reduction in markups caused by price regulation (Philipson and Durie (2021b)). To evaluate the magnitude of the reduction in effort caused by price caps, we analyze changes in the total number of promotional payments received by physicians at hospitals following 340b accreditation between 2014 and 2019 in a difference-in-differences framework. We find that physicians at newly-accredited 340b hospitals received 13% fewer promotional payments after their hospital joins the program, relative to physicians at non-340b hospitals with similar patient populations. At the average documented 340b discount of 47%

[1] Throughout this paper, we use the terms "promotional payments," "promotional effort," "detailing payments," and "promotional outreach" interchangeably. In Section 4, we discuss how the lack of data on non-payment detailing activities may affect the interpretation of our results as promotional effort.

[2] Qualifying for the 340b program requires that a hospital serve a large share of low-income patients. Since its inception in 1992, the 340b program has grown into an economically relevant feature of the US prescription drug market, with participating healthcare providers benefiting from $50 billion in cost savings through the program in 2021 alone (Fein (2020)).

(Fein (2020)), this estimate implies an average elasticity of promotional effort with respect to revenue of 0.26. A placebo exercise examines changes in promotional payments related to medical devices or supplies, which are not subject to discounts under the 340b program. Reassuringly, we do not find any changes in promotional payments related to these products following take-up of the 340b program by hospitals.

While overall decreases in promotional payments at newly-accredited 340b hospitals may be expected, we show that the design of discounts under the 340b program generates incentives for pharmaceutical firms to adjust promotional effort asymmetrically across drugs in their portfolios. That is, analyses of aggregated changes in promotional effort may obscure important heterogeneity in the responses for individual drugs. We analyze the role of one specific but important design feature of the 340b discount: a penalty that reduces a drug's price if past price adjustments have outstripped past rates of inflation. Most prescription drug prices have consistently outpaced inflation in nearly every year since their release, resulting in an ever-widening gap between current prices and the inflation-adjusted launch prices. Consequently, 340b discounts generally increase as drugs age. Thus, we expect that manufacturers will adjust their promotional efforts to physicians in 340b hospitals differentially across drugs based on variation in the size of the discounts across all drugs.

To illustrate how the design of the program influences the strategic responses of pharmaceutical firms, we present a model of promotional effort by a multi-product monopolist. We show that a multi-product firm that produces substitute drugs may shift promotional effort towards drugs that face smaller 340b discounts in order to reduce its exposure to the larger discounts mandated for other drugs. As a result, even though the firm may decrease promotional payments in response to the price caps overall, it may *increase* payments for some drugs in order to divert prescriptions from less profitable drugs to more profitable ones.[3] Combining this prediction with the inflation penalties described above, we expect that firms would decrease promotional effort for older drugs while potentially increasing efforts for newer, more profitable drugs.

To explore how firms adjust promotional effort across drugs, we estimate pharmaceutical firms' response to the 340b program separately for 163 on-patent drugs with the largest number of promotional payments during the sample period. We document decreases in promotional payments for many drugs, but increases for certain drugs. We observe the largest decreases in equilibrium promotional effort for drugs that have been on the market for more than five years (and are thus likely to face the largest inflation penalties); in contrast, most of the drugs for which we observe increases in effort are within their first five years of FDA approval. To better illustrate these responses, we examine promotional effort for drugs that treat diabetes, a condition that affects roughly 10% of Americans and accounts for 21% of promotional payments to physicians. We document reallocation from older to newer diabetes drugs within firms' portfolios of diabetes drugs at 340b hospitals relative to non-340b hospitals. We show that what seems like an obvious relationship between price and promotional effort in a single-product setting (i.e., a positive correlation between markups and promotion) can be reversed in a multi-product environment.

Our results suggest that the design of price regulations is an important determinant of pharmaceutical firm effort. Policymakers often design price regulations that create heterogeneous impacts across drugs. Much like the 340b program, the drug pricing provisions of the Inflation Reduction Act (IRA) introduced

[3]The change in prices induced by the 340b price caps has both a direct effect on firm profits through markups and an indirect effect through changes in demand, as hospitals may encourage physicians to switch prescriptions towards drugs with larger discounts, which are more profitable for the hospital.

penalties for raising drug prices faster than inflation; furthermore, they created exemptions from Medicare price negotiations for certain drugs, either outright or for a fixed time period following their introduction. Our analysis suggests that these design features of the IRA may induce manufacturers to substitute promotional effort across drugs. More broadly, we provide novel empirical evidence that price-based regulations targeted at one product may also influence the promotion of substitute products. This insight extends beyond the pharmaceutical sector. For example, policymakers may levy taxes to reduce consumer demand for unhealthy products, such as tobacco or soft drinks. In response, firms may strategically adjust advertising to steer consumers towards substitute products in their portfolios (e.g., vape products or juice). Recognizing these strategic, non-price adjustments is essential for policymakers seeking to design effective regulations targeting specific products.

There is an extensive literature in marketing and economics that measures the effects of pharmaceutical outreach to physicians on their prescription patterns (e.g., see Mizik and Jacobson (2004); Manchanda et al. (2008); Dong et al. (2009); Ching and Ishihara (2010); Ching et al. (2016); Montoya et al. (2010); Dong et al. (2011); Chintagunta et al. (2012); Datta and Dave (2017); Carey et al. (2021); Everhart et al. (2022); Marquardt and Ryan (2023)). In contrast, there is relatively less work on the process by which firms determine promotional strategies. In the health care sector, researchers have analyzed how detailing responds to new information about clinical effectiveness (Azoulay (2002); Lawler and Skira (2022); Shapiro (2018)) and to regulations on advertising (Guo et al. (2020, 2021); Larkin et al. (2017)). Agha and Zeltzer (2022) show that pharmaceutical firms target physicians with broad professional networks. In the grocery sector, Keller et al. (2024) leverage taxes on sugar-sweetened beverages and finds that retailers decrease promotional activities for sodas in response to taxes. The unique nature of the 340b program allows us to measure the effects of prices on marginal promotional incentives, and to provide novel evidence on how firms' equilibrium promotional efforts respond across substitute drugs.

We also contribute to the growing literature on the effects of the 340b drug pricing program. Research in this area has typically focused on how the 340b program affects hospitals, particularly their finances (Han (2018)) and organizational structure (Desai and McWilliams (2018)). A few papers also explore how the 340b program affects treatment decisions in the context of provider-administered drugs. Berger (2023) finds that hospitals increase infusions by 72% after joining the 340b program, and Bond et al. (2023) find that 340b providers are less likely than non-340b providers to switch from branded infused drugs to biosimilar drugs upon their entry, ostensibly because biosimilars are not covered by the 340b program. Gray (2023) and Bruno et al. (2024) also examine the impacts of 340b expansions on insurance plan design in Medicare Part D. To the best of our knowledge, we are the first paper to examine how this program affects the strategic behavior of pharmaceutical firms. Our findings that price regulation affects incentives to exert promotional effort mirror findings from empirical studies of how prices influence investment in quality (Yurukoglu et al. (2017)) and research and development (Ji and Rogers (2024); Philipson and Durie (2021a)).

The rest of the paper is organized as follows. Section 2 provides an overview of the regulatory setting. Section 3 describes our data. Section 4 describes our estimation strategy and presents results from our hospital-level analyses. Section 5 presents our model of optimal allocation of promotional effort. Section 6 presents results from our drug-level analyses. Section 7 concludes.

2 The 340b Drug Pricing Program

The 340b Drug Pricing Program was enacted by Congress in 1992. Hospitals qualify for the 340b program if they (a) are either non-profit or government-owned, and (b) serve a large share of low-income patients.[4] The second condition requires that hospitals have a disproportionate share adjustment percentage (DSH %) greater than 11.75% on their most-recently filed cost report. This threshold is relaxed to 8% for rural referral centers and sole community hospitals. The DSH % measures the hospital's share of total patient volume that is either covered by Medicaid or covered by Medicare and receiving supplemental security income.

The 340b program was designed to create a new profit stream for hospitals by reducing the marginal costs of dispensing outpatient drugs. The program requires drug manufacturers that participate in Medicaid to provide outpatient drugs to 340b hospitals at discounted prices. Policymakers believed the program would generate new profits for hospitals that would in turn allow them to expand service lines and handle a greater volume of patients. In 2019, more than 2,500 hospitals participated in the program and, combined, made nearly $30 billion in outpatient drug purchases through the program (Fein (2020)).

For each drug, the program defines a uniform ceiling price, which sets a cap on the price that firms can charge to 340b hospitals. The ceiling price for each drug is determined by taking the average price paid by wholesalers, as reported to the Centers for Medicare and Medicaid Services (CMS), and reducing it by a unit rebate amount. The unit rebate consists of two parts: a basic rebate and an additional rebate. The basic rebate grants participating hospitals most-favored-nation status: they receive the largest discount granted by the manufacturer to any purchaser.[5] The additional rebate penalizes drugs for raising list prices faster than inflation: each drug must pay an additional rebate equal to the difference between the list price reported to CMS and an inflation-adjusted version of the list price at the time of the drug's initial release.

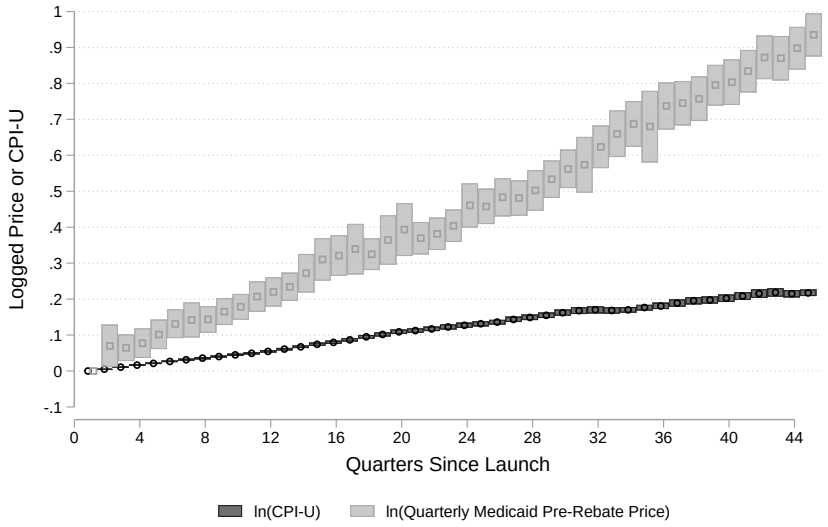
We do not have access to data on the 340b ceiling prices or list prices, which are confidential; thus, we cannot observe or estimate the total 340b discounts for each drug. However, we can approximate how the inflation penalty evolves over the life-cycle of a drug using the Medicaid State Drug Utilization Data maintained by CMS, which reports quarterly pre-rebate spending and prescriptions by drug for each state.[6] In Figure 1, we show the evolution of pre-rebate prices paid to pharmacies and other providers for a set of diabetes drugs that we observe in our advertising data, which we use as proxy for list prices. Pre-rebate prices increase by roughly 80% on average ten years after launch. In contrast, the Urban Consumer Price Index increased by 20% on average over the same ten-year period. These divergent price series imply that the inflation penalties increase over a drug's lifetime. For example, these series imply that for the average drug, the inflation penalty adds up to over $6 per unit (e.g., per dose or pill) five years after a drug's launch, or 22.1% of the average pre-rebate price.

[4] Qualifying providers also include federally qualified health centers and other specialized clinics. We focus our attention on hospitals, because the other provider types account for a much smaller share of patient volume.

[5] The basic rebate is implemented as the maximum of (1) the difference between the average manufacturer price (AMP) and the lowest price available from the manufacturer during the period to any other purchaser in the US and (2) 23.1% of AMP. The AMP is the average price paid by wholesalers for a given drug, as reported to CMS each quarter. We refer to the AMP as the list price throughout, as we understand that wholesalers play a limited role in determining the prices of branded drugs.

[6] These pre-rebate prices include dispensing fees and any additional pharmacy markups, and thus represent an approximation of the AMP used to determine 340b rebates.

Figure 1: **Evolution of Medicaid Prices and CPI-U for Diabetes Drugs**



Sources: Medicaid State Drug Utilization Data; OpenPayments Data; FDA NDC Database.
Notes: analysis was limited to the diabetes drugs that we identified in the OpenPayments data. Both panels show changes in outcomes relative to the drug's launch quarter. The level of observation in the SDUD is an drug-quarter-year, where the drug is identified based on their ten-digit National Drug Code (NDC). Drugs can have different NDCs for different package sizes. We define a price per unit rather than per prescription to account for different package sizes across NDCs within a drug.

While we cannot precisely estimate the magnitude of the 340b discounts by drug, we expect that overall 340b discounts grow over a drug's life cycle, and we use this pattern to interpret our empirical results. In principle, drug manufacturers could adjust their list prices in response to major expansions of the 340b program, or reduce basic rebates as a drug ages to counteract the growing inflation penalties. We believe it is unlikely that either list prices or negotiated rebates would change in response to the take-up events that we exploit in the empirical analysis. The expansions we study are geographically dispersed and small in scale relative to the overall drug market, lacking the scale necessary to influence broader pricing strategies. Furthermore, rebates (and thus 340b basic rebates) are negotiated nationally, and typically increase over a drug's life-cycle (Kakani et al. (2020)), which would also result in larger 340b discounts for older drugs.

To capture the benefits from the program, outpatient drugs need to be dispensed either through the participating hospital's own pharmacy or through third-party "contract pharmacies." Contract pharmacies are retail or mail-order pharmacies (e.g., CVS, Walgreens) that partner with hospitals to dispense drugs purchased through the 340b program. Before 2010, 340b hospitals were limited to working with a single contract pharmacy. In 2010, the government permitted 340b hospitals to use an unlimited number of contract pharmacies. The number of retail pharmacies working as a contract pharmacy for 340b providers has grown from fewer than 5,000 in 2010 to nearly 30,000 in 2020 (Mulligan (2021)). 49.9% of Medicare Part D prescriptions written by 340b providers were filled at contract pharmacies in 2020 (Dickson et al. (2023)); thus, 340b hospitals obtain discounts on a significant share of prescriptions written by their affiliated physicians.[7]

[7]Prior to the change in contract pharmacy policy, many hospitals may have been limited to obtaining 340b discounts on provider-administered drugs, such as cancer treatments that are infused under supervision of a healthcare professional. After the contract pharmacy expansion, hospitals could take advantage of the program for more prescriptions of self-administered drugs, which

Anecdotal evidence suggests that 340b drug discounts are large and affect producers' markups directly. Drug manufacturers have advocated for reforms of the 340b program, particularly the use of contract pharmacies. Since 2020, at least twelve pharmaceutical firms have announced that they would no longer provide 340b-discounted products to contract pharmacies, leading to litigation between the government and drugmakers (King (2022); Pierson (2023)). These actions suggest that the design of the 340b program significantly reduces the profits earned by pharmaceutical firms. Therefore, the program is likely to change the incentives of pharmaceutical firms to exert promotional effort, which we measure using data on in-kind transfers from pharmaceutical firms to physicians.

3 Data

In 2010, Congress enacted the Physician Payments Sunshine Act (hereinafter "the Sunshine Act") as part of the Affordable Care Act. The Sunshine Act required manufacturers of pharmaceuticals and medical devices to disclose all transfers made to physicians and teaching hospitals to CMS. CMS publishes all such records in the publicly available Open Payments (OP) dataset, which we use in our analysis. For every transfer, the OP data identify the firm who made the payment, the physician who received the payment, the dollar amount of the transfer, all products discussed during the meeting, the form of payment (e.g., cash or cash equivalent, in-kind items and services), nature of payment (e.g., food and beverage, travel and lodging), and the date of the payment.

The main drawback of the OP dataset is that it only covers physician payments and does not allow us to observe other promotional activities, such as e-mails, samples, and physical mail. While other papers have more complete data on the detailing relationships between certain drug manufacturers and physicians that capture non-payment detailing interactions, such data are typically restricted to one class of drugs or to physicians practicing outside of the United States (e.g., Manchanda et al. (2008); Dong et al. (2009); Narayanan and Manchanda (2009); Ching and Ishihara (2010); Dong et al. (2011); Ching and Ishihara (2012); Liu et al. (2016)). These detailed data are important for understanding the effects of promotion to physicians on their prescription patterns. An important advantage of our dataset is that it covers both the universes of pharmaceutical manufacturers and of physicians in the U.S., which are important to observe in order to answer our research question. In Section 4, we discuss how the lack of data on non-payment detailing activities may affect the interpretation of our results as promotional effort.

We combine the OP data with information on drugs, physicians, and hospitals. To identify the release date of each drug, we combine the information in the OP data with the National Drug Code database maintained by the US Food and Drug Administration. Our universe of physicians comes from the CMS National Downloadable File data for 2014 to 2019, which includes information on physicians' practice specialties and hospital affiliations. We assign each physician to a hospital in each year based on their first listed hospital affiliation in the National Downloadable File for that year, which we understand represents their "primary" hospital affiliation. Our implicit assumption is that pharmaceutical firms consider this primary hospital affil-

consumers obtain through a retail pharmacy. These self-administered drugs are the focus of our analyses because they are the largest advertisers to physicians in our data.

iation when making promotional decisions, as most of the physician's patients will use that hospital. In most of our analyses, we exclude physicians who were not affiliated with a hospital, and aggregate payments up to the hospital-level to be consistent with the variation in 340b participation.

Our hospital information comes from three sources: (1) the CMS Hospital Cost Reporting Information System, (2) the CMS Provider of Services data, and (3) the Health Resources and Services Administration Office of Pharmacy Affairs Covered Entity and Contract Pharmacies data. The first dataset details the facility type, disproportionate share percentage (DSH %), beds, rural status, program participation, and tax status (for-profit vs. non-profit). The second dataset provides information on the hospital's location. The third dataset contains information on 340b program participants (commonly referred to as "covered entities") separately for each hospital, including participation history and the identities of all contract pharmacy relationships. We define a hospital as participating in the 340b program in a given quarter if the hospital or any of its affiliated outpatient clinics were participating in the program.

3.1 Sample and Summary Statistics

The OP data are available from January 2014 through December 2019. Consistent with prior research, we focus on records of food and beverage payments, which accounted for 91% of promotional payments in the first quarter of 2014 (Lawler and Skira (2022); Grennan et al. (2021)). We restrict our sample to physicians who were affiliated with hospitals, and to hospitals that appear in the data in every year 2014-2019 in order to avoid detecting changes in physician payments due to closures. The treatment variation is at the hospital level so our analyses aggregate the data across physicians to the hospital level. Our analyses focus on short-term general acute care hospitals, sole community hospitals, and rural referral centers. We provide more information in the data appendix.

Table 1 summarizes physician payments from pharmaceutical firms separately for 2014q1 and 2019q1. Pharmaceutical representatives may discuss multiple drugs during a single detailing visit: 27% of the transfers in our data list more than one product. For our analyses at the hospital level of observation, we count a payment only once, regardless of the number of products associated with the payment. For our product-level analyses, we count a payment once for each product associated with the payment.

Table 1: **Physician Payments Summary Statistics**

	2014q1	2019q1
Total Number of Payments	2,019,870	1,912,232
Total Meal Payments	1,847,479	1,769,174
$ per Meal	19.56	20.37
Number of Advertising Drugs	1,162	1,197
Avg. # of Payments per Drug	2,246.8	1,913.6
	(7,527.7)	(5,965.8)
% of Payments by Top 163 Drugs	0.548	0.668
Avg. # of Payments per Top Drug	12,338.7	9,618.3
	(16,995.7)	(12,265.7)
Number of Advertising Firms	225	292
% of Payments by Top 70 Firms	0.955	0.903
Avg. Number of Drugs in Top Firm Portfolio	12.59	12.76
	(13.8)	(12.9)

We observe payments related to 1,162 drugs in the first quarter of 2014; however, the vast majority of payments come from a subset of high-advertising drugs in the data. When studying heterogeneous effects across drugs, we focus on a sample of 163 "top" on-patent drugs, which account for around 65% of payments.[8] The average "top" drug made 12,338 detailing payments to physicians in 2014q1. We observe 225 pharmaceutical firms making payments in 2014q1, and we focus on the top 70 firms, which account for over 90% of food and beverage payments. These firms promote roughly 12 different drugs in a given quarter.

From an empirical standpoint, these data on promotional payments, combined with variation in the 340b program across hospitals and time, allow us to infer how pharmaceutical firms' provision of promotional effort responds to changes in prices. Notably, we observe differences in promotional payments for the same drug across physicians, which allows us to credibly measure how price caps affect the marginal promotional incentives of pharmaceutical firms.[9]

[8] We subset the data in this manner because we may not be able to identify an effect of the 340b program on promotional payments for drugs that either do not advertise regularly during our data sample or make few payments. Our sample consists of the top 163 on-patent drugs based on average quarterly promotional payment volume, plus all on-patent diabetes drugs regardless of their level of promotional payments. This definition left us with 163 drugs. We drop drugs that lost patent protection before or during our study period to avoid detecting changes in promotional activity driven by confounding drug-specific factors, such as generic entry.

[9] Our setting allows us to contribute to earlier studies of nationally-implemented regulatory or market changes (such as patent expirations), which often involve making comparisons across potentially very different drugs, or studying changes to pharmaceutical firm markups that are correlated with demand shocks (Scott Morton (2000); Shapiro (2016); Van Der Schans et al. (2021); Regan (2008); Frank and Salkever (1992); Kwong and Norton (2007)).

4 Hospital-Level Analysis

4.1 Estimation

We begin our empirical analysis by studying how the 340b program affects the overall number of promotional payments received by physicians at participating hospitals. We exploit variation in 340b participation across time and hospitals in a difference-in-differences framework to examine how pharmaceutical firms adjust their advertising strategies in response to drug pricing regulations. Our estimating equation is

$$Payments_{ht} = \beta 340b_{ht} + \alpha_h + \alpha_t + \varepsilon_{ht}, \tag{1}$$

where $Payments_{ht}$ is the number of payments from pharmaceutical firms received by physicians at hospital h in quarter t, $340b_{ht}$ is an indicator variable equal to one in all quarters in which hospital h participated in the 340b program, and α_h and α_t are hospital and time fixed-effects. We also estimate an event study version of Equation (1):

$$Payments_{ht} = \sum_{l=-8}^{8} \beta^l D_{ht}^l + \alpha_h + \alpha_t + \varepsilon_{ht}, \tag{2}$$

where D_{ht}^l is an indicator that is equal to one if and only if hospital h is l quarters from taking up the 340b program at time t. We estimate Equation (1) and Equation (2) using the estimator from Sun and Abraham (2021) to account for staggered timing in the adoption of the 340b program.

Our treatment group includes 115 hospitals that began participating in the 340b program for the first time between January 2016 and March 2018. We focus on hospitals gaining status during this period because the OP data cover 2014-2019, and we want to observe a hospital for at least two years before and after treatment. There are 1,575 hospitals that did not participate in the 340b program at any point between 2014-2019. We construct a control group by making two restrictions. First, in order to study hospitals with roughly similar patient populations, we restrict our control group to hospitals that were eligible for the 340b program in at least one quarter of our sample period but did not get 340b accreditation during the analyzed time period.[10] Second, we exclude non-340b hospitals that are in the same hospital service area (HSA) as any of our 115 treated hospitals.[11] These two sample restrictions leave us with a control group of 267 hospitals. We check that our results are robust to alternative control group definitions in the appendix.

Table 2 displays summary statistics for the first quarter of 2014 for treatment and control hospitals. Hospitals that gain 340b status during our sample period tend to be larger in terms of the number of beds and the number of employed medical professionals relative to the set of control hospitals. After controlling for size, our treatment and control hospitals are roughly similar in terms of the amount of detailing payments

[10] We exclude hospitals that were in the 340b program for the entirety of our sample ("always-treated" hospitals). Table A.1 presents the same summary statistics from Table 2 but for the 890 always-treated general acute care (GAC) hospitals that are active in all quarters 2014-2019. The always-treated hospitals are slightly larger than our treatment hospitals, but write fewer Part D prescriptions and serve lower-income patient populations as measured by the DSH %. We also exclude hospitals that experienced a lapse in 340b participation ("sometimes-treated" hospitals). There are 228 hospitals that we manually identified as experiencing a lapse in 340b participation, likely because they were unable to meet the qualification criteria.

[11] Hospital Service Areas are sets of zipcodes whose Medicare residents receive most of their hospitalizations at hospitals located in that area (Dartmouth Atlas).

and prescriptions. In addition, our empirical analyses control for differences in levels using hospital fixed effects.

Table 2: **Hospital-Level Summary Statistics, 2014q1**

	(1) Treatment		(2) Control		(3) Difference		
	Mean	SD	Mean	SD	Difference	SE	P-Value
# of Professionals	237.91	283.68	98.28	150.93	-139.63	22.33	0.000
# of Beds	246.44	283.26	104.40	128.90	-142.03	21.08	0.000
# of Part D Prescriptions per Professional	3835.88	3422.18	3503.97	2502.61	-331.91	313.45	0.290
# of Promotional Payments per Professional - Drugs	2.87	2.07	2.35	2.16	-0.52	0.24	0.031
# of Promotional Payments per Professional - Device	0.43	0.28	0.35	0.47	-0.08	0.05	0.080
$ of Promotional Payments per Professional - Drugs	49.20	31.88	40.35	35.41	-8.85	3.84	0.022
$ of Promotional Payments per Professional - Device	17.99	13.04	14.04	20.39	-3.95	2.06	0.057
DSH %	0.15	0.41	0.14	0.16	-0.01	0.03	0.772
1(Rural Hospital)	0.30	0.46	0.41	0.49	0.12	0.05	0.031
Observations	115		267		382		

Notes: the unit of observation is a hospital. We limit promotional payments to food and beverage payments. Details on the construction of the DSH % and other data cleaning assumptions are in the data appendix.

4.2 Identification

We seek to identify the effect of 340b participation on the number of promotional payments. Our primary identifying assumption is that promotional payments to physicians at treatment hospitals would have followed the same trend as control hospitals absent their take-up of the 340b program. We also make the standard assumptions that treatment is irreversible and that it does not affect outcomes in periods before the hospitals join the 340b program. We face three potential threats to identification. First, take-up of 340b may be correlated with other important changes at the hospital that independently affect the promotional incentives of pharmaceutical firms. Second, take-up of the 340b program may have spillover effects on firms' promotional incentives at non-340b control hospitals, which would violate the stable underlying treated values assumption (SUTVA) of our difference-in-differences estimator. Finally, we do not observe if pharmaceutical firms adjust other detailing efforts not tied to an in-kind transfer. We describe each of these concerns below.[12]

Selection of hospitals into treatment

Take-up of the 340b program may be correlated with factors that affect both the selection of hospitals into the program and the intensity of pharmaceutical firms' promotional effort at those hospitals. For example, hospitals may join the program due to financial distress or after a restructuring, which may independently lead to a change in payments from pharmaceutical firms. Conversely, newly-designated 340b hospitals may strategically adjust their patient mix or use the revenue generated by the 340b program to invest in expanded

[12] Another concern relates to pharmaceutical firms anticipating take-up of the 340b program by hospitals. The event study specifications provide graphical evidence that trends in physician payments were similar for treated and control hospitals in the quarters prior to the adoption of the program.

healthcare offerings, which could lead to changes in promotional payments.[13] The first scenario challenges our identifying assumptions, while the second scenario primarily changes the interpretation of our results from the effects of price regulation on promotional effort to the effects of the 340b program more broadly.

We evaluate these concerns in several ways. First, we use payments from medical device manufacturers as a placebo group. These products are not covered by the 340b program and medical device firms do not sell drugs. If hospitals take up the 340b program because they are in financial distress or, conversely, because they plan to expand their operations, we should observe that medical device manufacturers will adjust their promotional activity at treated hospitals, because those changes will affect their returns to promotional activity as well. Changes in the promotional strategies of medical device manufacturers could suggest that take-up of the 340b program is correlated with other important changes at the hospital.

Second, we repeat our analyses with added controls for time-varying hospital level covariates to evaluate the concern that treated hospitals may change their physician and patient mix after taking up the program, which may change firms' returns to promotional activity separately from the pricing regulation. Specifically, we control for changes over time in a hospital's patient mix (using the DSH %), the size of the hospital (using total hospital beds), and the number of physicians affiliated with the hospital.

As seen in Table 2, treated hospitals are larger than control hospitals, even though prescriptions and promotional payments per physician match up nicely. Hospital fixed effects can address time-invariant differences across hospitals; however, covariate imbalance may raise concerns about selection into treatment on both observable and unobservable characteristics. We use a synthetic control approach that allows us to compare newly accredited 340b hospitals to hospitals with similar characteristics. For each treated hospital, we construct a synthetic control hospital from the set of never-treated hospitals (excluding hospitals in the same HSA as a treatment hospital) by matching on pre-treatment quarterly promotional payments, DSH %, beds, and number of medical professionals.

It is natural to wonder why the eligible hospitals in our control group choose not to join the program. One of the primary qualifications for 340b participation is patient mix, as measured by the DSH %. Hospitals experience variability in their patient mix, which may change their eligibility for the program over time and influence their decisions on whether to apply for 340b accreditation. Consistent with this, only 24% of our control hospitals are eligible for the program in all quarters of our data. Apart from the eligibility criteria, our understanding is that there are administrative costs associated with joining and participating in 340b. Thus, hospitals may not be willing to pay a sunk cost of joining the program if they do not believe they can remain in the program long enough to recover it.

Spillovers effects on other hospitals

A second potential threat to identification is that firms may respond to 340b take-up by reallocating promotional effort across hospitals. As a result, expansions of the 340b program may have spillover effects on non-340b control hospitals. For example, if firms face fixed costs of detailing in an area, then the decision of whether and how often to make promotional payments to physicians in one hospital may affect

[13] For example, Desai and McWilliams (2018) shows that 340b participation is associated with ownership of more outpatient oncology clinics, and Han (2018) shows that the 340b program allows hospitals to better meet operating expenses.

promotional outreach to physicians in a nearby hospital. We assume that these potential spillovers (and resulting biases) are local in nature and would affect promotional payments only at hospitals that are located near newly-designated 340b hospitals.[14] We account for local spillover effects through the construction of our control group, which excludes hospitals located in the same HSA as a hospital in our treatment group. In the appendix, we estimate the local spillover effects of 340b participation on non-340b hospitals. Our identification assumption is that there are no geographic spillovers across HSA regions. This assumption would be violated if pharmaceutical firms shift promotional effort from one region to another in response to growth in the 340b program. While we are unable to verify whether this identification assumption holds using our data, we confirm that our results hold if we account for potential spillovers at more distant hospitals by dropping control hospitals in the same hospital referral region (HRR) as our treatment group hospitals.[15] The results are reported in the appendix.

In many markets, changes in prices cause consumer substitution across suppliers. Such substitution patterns are unlikely to be a concern in our setting for two main reasons. First, the 340b program transfers funds from the manufacturer to the participating hospital by putting a cap on the wholesale price, while the final price paid by insurers and patients remains the same. Second, even if the discounts were passed through in lower prices, we are not aware of any evidence that patients consider prescription prices to be an important factor in choosing a physician or hospital.

Data limitations

Our data allow us to estimate how the 340b program affects the volume of promotional payments received by physicians at participating hospitals, which we use to proxy for the overall provision of promotional effort by pharmaceutical firms. A limitation of our data is that we do not observe firms' promotional outreach to physicians that are not connected to an in-kind transfer. Thus, one may worry that pharmaceutical firms may substitute away from physician payments at newly 340b hospitals to other, non-payment forms of detailing, such as mailing, phone calls, or free samples.

Whether this data limitation introduces bias in our estimates depends on how targeted the non-payment detailing efforts are. If non-measured promotional effort (such as emails) is not targeted to physicians in a way that depends on their employment by certain hospitals, then we would not expect it to change after a hospital gains 340b accreditation. For other targeted forms of promotional effort (e.g., free samples), it is not obvious whether pharmaceutical firms consider these alternative advertising forms to be substitutes or complements to promotional payments. If they are complements, then we would expect targeted, non-payment detailing to decrease as well, which would reinforce our results. If they are substitutes, then our results would still present evidence of pharmaceutical firms shifting effort towards (presumably) lower-value forms of detailing. Unfortunately, we could not find any empirical documentation of the correlation between payment and non-payment promotional activities by pharmaceutical firms. We acknowledge that non-payment forms of detailing may also adjust to the 340b program, depending on their costs and degree

[14] Grennan et al. (2021) and Larkin et al. (2017) show that the conflict of interest policies of academic medical centers causes neighboring physicians to receive fewer promotional payments. These authors attribute the spillover effects on promotional payments to economies of scale in salesforce allocation.

[15] HRRs are broader geographic markets for hospital care than HSAs.

of targeting.

4.3 Results

Table 3 presents the hospital-level regression results for Equation (1). We observe that physicians receive about 47 fewer promotional payments per quarter from pharmaceutical firms after their affiliate hospital joins the 340b program, a 13% decrease off of the sample mean. We can use this estimated treatment effect and an average reported 340b discount of 47% (Fein (2020)) to calculate an elasticity that quantifies how promotional payments to physicians adjust in response to changes in revenue. Our estimates imply an average elasticity of promotional effort to revenue of 0.26. To our knowledge, this is the first paper to measure such an elasticity.

Table 3: **Effect of 340b Participation on Quarterly Physician Payments, Hospital-Level**

	Drugs	Drugs, Keep Nearby Control Hospitals	Medical Devices + Supplies
340b	–46.7***	–43.9***	2.47
	(16.4)	(16.4)	(3.07)
Observations	9,168	9,648	9,648
Sample Average	354	353	64.3

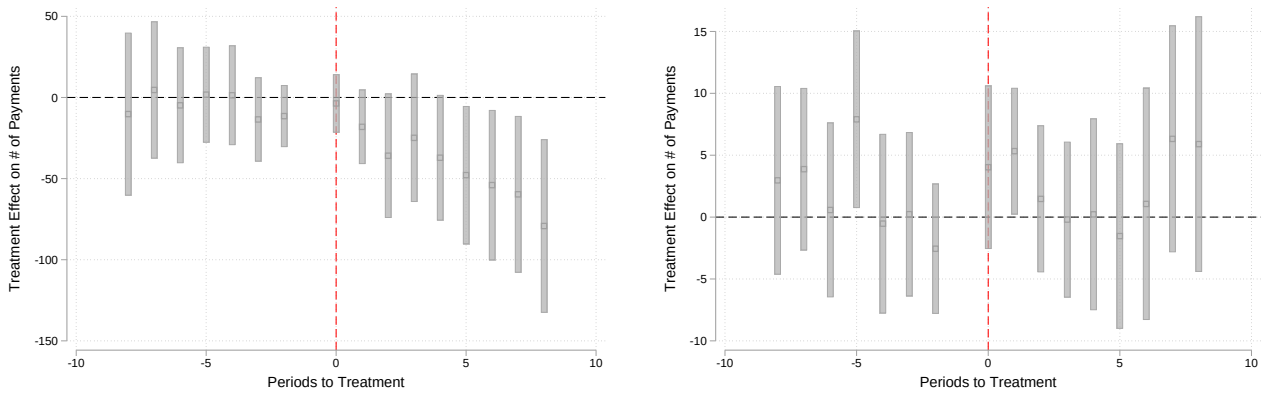
Notes: Standard errors in parentheses are clustered by hospital. Regressions were estimated using Sun and Abraham (2021) to account for staggered treatment timing. We report the average treatment effect on the treated for all treatment cohorts across all treatment periods. * p<0.10, ** p<0.05, *** p<0.01

In Column 2, we report the estimated treatment effect when we do not restrict the set of control hospitals to only include hospitals that are not in the same HSAs as a hospital in our treatment group. Comparing the results between the two estimation approaches allows us to sign and evaluate the magnitude of the potential bias from a SUTVA violation. We see that ignoring these spillovers produces a slightly less negative estimate of treatment effects. This is consistent with the presence of small reductions in promotional payments at non-340b hospitals that are located in the same HSAs as newly-accredited 340b hospitals. Column 3 of Table 3 reports results of estimates for our placebo regression, where we study how take-up of the 340b program affects promotional payments by medical device and supply manufacturers. Reassuringly, we find no effect of 340b participation on physician payments by these firms. In Table A.2 and Table A.3, we show that our results hold if we further restrict our control group to exclude control hospitals in the same hospital referral region as our treatment group hospitals, or if we loosen our control group definition to include all non-340b hospitals.

Figure 2 presents the event study versions of the hospital-level regressions from Equation (2). The event studies demonstrate that promotional payments for both drugs and devices/supplies were trending similarly at treatment and control hospitals prior to the treatment. Figure A.1 confirms the robustness of our estimates when accounting for time-varying hospital covariates, and Figure A.2 provides the event study results from our synthetic control analyses.

The event studies show that promotional payments gradually decline following take-up of the 340b pro-

Figure 2: **Event Study of 340b Participation on Quarterly Physician Payments, Hospital-Level**



(a) Drugs (b) Medical Devices and Supplies Placebo

Notes: Standard errors are clustered by hospital. All specifications include hospital and year-quarter fixed effects. Regression was estimated using Sun and Abraham (2021) to account for staggered treatment timing. We report the average treatment effect on the treated across all treatment cohorts relative to the quarter before treatment.

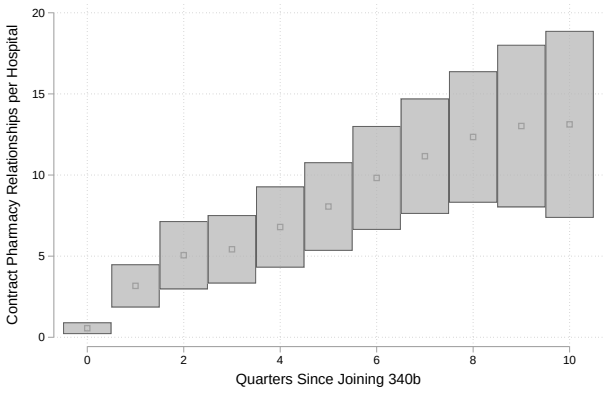
gram. One explanation for these gradual adjustments is that it takes time for newly-accredited 340b hospitals to develop a network of contract pharmacies to fully take advantage of the discounts. Hospitals can take advantage of the steep discounts if they sell the drugs to patients either at their facility or through contract pharmacies. We observe that our treated hospitals gradually increase their number of contract pharmacy relationships after joining the 340b program. Figure 3 shows the average number of contract pharmacy relationships in each quarter following take-up of the 340b program for our treatment hospitals. As hospitals expand their contract pharmacy network, one expects that a larger share of prescription fills are shifted towards the discounted price, decreasing the average margin for drugs prescribed by 340b physicians. Therefore, the increase in contract pharmacies over time implies a decrease in average margins at 340b hospitals over time, which is consistent with the gradual decrease in effort towards our set of treated hospitals.[16]

These hospital-level analyses demonstrate that pharmaceutical firms reduce overall promotional payments at newly-accredited 340b hospitals. The equilibrium adjustment that we measure is the combination of both a direct effect of price caps on promotional payments through reduced markups, and an indirect effect through changes in prescription volumes, as the price caps may shift prescribing patterns. Hospitals are not passive participants and may incentivize physicians to steer prescriptions towards more profitable drugs. If demand for a drug increases due to these incentives, the firm may no longer need to promote it to boost prescriptions. While economists have shown evidence that 340b providers strategically increase their use of provider-administered drugs (Berger (2023); Bond et al. (2023)), we are not aware of any evidence on how the 340b program affects prescription volumes for self-administered drugs.[17] Overall, our findings indicate

[16] We acknowledge that this is one potential explanation for the dynamic trend that we observe. Another reason why we may observe a gradual decline is that the 340b discounts faced by pharmaceutical firms grow over time due to inflation penalties. We do not test between potential theories but rather provide suggestive evidence as to one of the mechanisms that may drive the patterns we observe in the data.

[17] Our analysis focuses on self-administered drugs because they are the largest advertisers to physicians in our data, while we do not observe much promotional activity (in terms of physician payments) for provider-administered drugs.

Figure 3: **Utilization of Contract Pharmacies by Treatment Hospitals**



Sources: HRSA OPAIS data. Notes: this graph shows the average number of contract pharmacy relationships in each quarter following take-up of the 340b program for our treatment hospitals. The grey bars represent 95% confidence intervals.

that pharmaceutical firms adjust their promotional strategies in response to the 340B program's price caps.

5 Optimal Promotional Effort

The results in Section 4 illustrate that pharmaceutical firms adjust promotional effort in response to expansions of the 340b program. Because the inflation penalties generate variation in the discounts across drugs, we should expect that manufacturers adjust effort differentially across drugs. In this section, we develop a theoretical model of strategic promotional effort to illustrate how the design of the 340b discounts changes the incentives of pharmaceutical firms to advertise to physicians. We analyze the decisions of a multi-product monopolist who chooses promotional payments for each of its drugs. As prices are set nationally and our empirical analysis exploits small, local expansions of the program, the theoretical model takes prices as given. We allow regulation to affect markups differently across drugs and show that this heterogeneity induces corresponding adjustments to promotional effort across drugs.

We model the firm's promotional payments across drugs in a single hospital. We abstract away from consumer choices of physicians and hospitals in our model, as we do not believe those choices to depend on physician prescribing patterns, 340b discounts, or promotional payments. This feature of the market implies that a pharmaceutical firm cannot reduce its exposure to the 340b program by increasing advertising at non-340b hospitals. Consider a firm that sells two differentiated drugs $j \in \{1,2\}$ and its profits are defined as:

$$\Pi(\mathbf{p},\mathbf{a}) = \sum_{j=1,2} D_j(\mathbf{p},\mathbf{a})(p_j - c) - w * a_j, \tag{3}$$

where $D_j(\mathbf{p},\mathbf{a})$ is demand for drug j (which depends on the prices and promotional effort of both drugs), c is the marginal cost of production, and w is the marginal cost of promotional effort. We consider a static one-period game: the firm simultaneously chooses a_j for both products, taking prices p_j as given.

Maximizing Equation (3) with respect to a_j provides the first order conditions that determine equilibrium

levels of promotion:

$$\sum_{k=1,2} \frac{\partial D_k}{\partial a_j}(p_k - c) = w. \tag{4}$$

This optimality condition demonstrates that promotional payments for drug j depends on both its own markup and the markup of the other drug k.

When a hospital joins the 340b program, the firm faces mandated discounts that lower the prices for both of its drugs. Given these new prices, the firm would likely re-optimize its promotional effort. The response of drug j depends on two factors: the post-regulation prices for both drugs and the cross-promotional effects $\frac{\partial D_k}{\partial a_j}$. Consider the case where the 340b-mandated discount for drug k is larger than that of drug j. If $\frac{\partial D_k}{\partial a_j} < 0$, then the firm may want to increase promotional effort for drug j if its markup is sufficiently larger than drug k's. This strategy may be optimal because promotional effort for drug j can be used to divert sales from the less profitable drug k. In contrast, if $\frac{\partial D_k}{\partial a_j} \geq 0$, such that promotion of drug j has positive spillovers on drug k, then the firm will not increase post-regulation promotional activity for drug j.

A numerical simulation helps us to illustrate these points. We use a linear demand function described as:

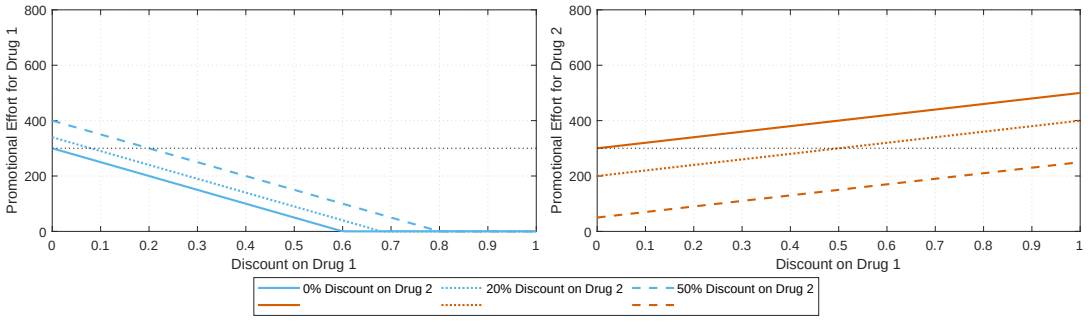
$$q_j = \gamma + \beta_1 p_j + \beta_2 p_k + \beta_3 log(a_j) + \beta_4 log(a_k). \tag{5}$$

First, we set prices and parameter values for the two drugs such that, absent 340b discounts, the "pre-discount" detailing efforts of the two products are symmetric. Then, we plot how optimal promotional effort changes as the discounts for each drug increase. The graphs in Figure 4 plot the optimal levels of promotion (a_1, a_2) plotted on the y-axis and the discount set by the 340b program for drug 1 on the x-axis. In each graph, we plot three lines that vary the discount for drug 2 to be 0%, 20% and 50%. We focus on the response of drug 1, shown in the left panels and optimal effort for drug 2 is plotted in the right panels for completeness. The horizontal black dotted line denotes the firm's optimal level of promotional effort absent price regulation; that is, optimal effort levels above that line indicate an increase in effort relative to the effort level chosen without the government mandated discounts. We consider three different cases to illustrate when price regulation may lead to increases or decreases in promotional activity of both drugs.

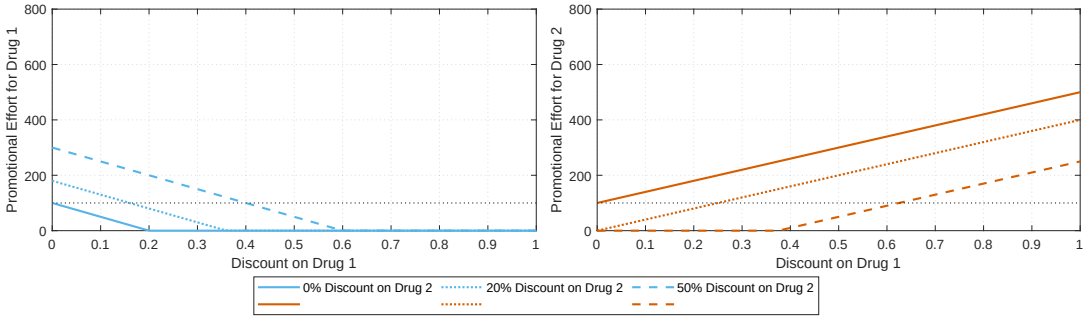
The first panel shows the scenario where we set $\gamma = 1000, \beta_3 = 5$, and $\beta_4 = -2$, such that the cross-promotional effect $\frac{\partial D_k}{\partial a_j}$ is negative. As expected, we see that promotional effort decreases as the drug faces higher discounts. We also see the expected increasing relationship between promotional effort and the discount of the other drug (because $\frac{\partial D_k}{\partial a_j} < 0$). Comparing across the three lines in panel (a), we see that there are values for which the promotional effort for drug 1 is higher than its promotion absent the price caps. When drug 1's discount is sufficiently small relative to drug 2's discount, the firm may prefer to increase promotional effort for drug 1 in order to divert demand to the more profitable product, even if the level of its markup has decreased. For example, when drug 2 faces a 50% discount, we see that drug 1 increases promotional activity above pre-cap levels as long as its discount is less than 20%.

The other two panels of Figure 4 show how these reallocation effects change as the substitution between the two drugs changes. In our simple setting, which keeps prices fixed, we capture substitution between the two drugs with $\frac{\partial D_k}{\partial a_j}$. In panel (b), we allow that drugs may be more substitutable by changing the β_4 parameter from -2 to -4, such that the cross-promotional effects are stronger. While the stronger cross-

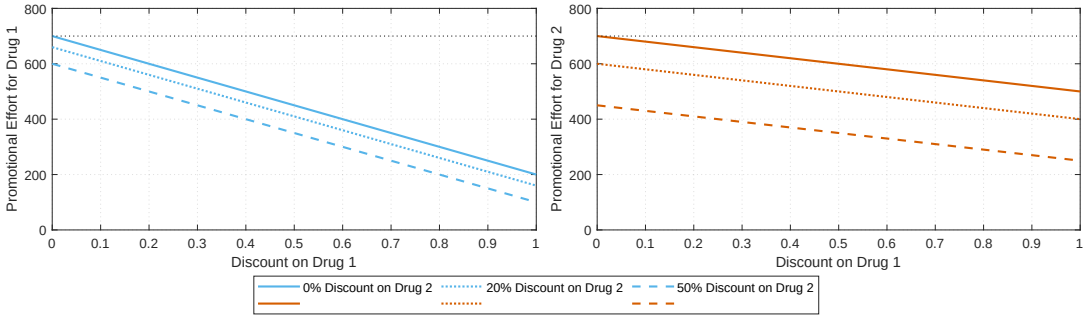
Figure 4: **Model Simulation**



(a) Base Case ($\beta_3 = 5, \beta_4 = -2$)



(b) Increase Cross-Promotional Effect ($\beta_3 = 5, \beta_4 = -4$)



(c) Positive Cross-Promotional Effect ($\beta_3 = 5, \beta_4 = 2$)

Note: we parameterize demand for good j as $D_j = \gamma_j + \beta_1 p_j + \beta_2 p_{-j} + \beta_3 log(a_j) + \beta_4 log(a_{-j})$. In equilibrium, $a_j = \beta_3 p_j - \beta_4 p_{-j}$. We set $\gamma_j = 1000 \beta_1 = -0.5, \beta_2 = 0.25, p_1 = p_2 = 100$ in all simulations. The left panels depict how promotional effort for drug 1 depends on the discount on drug 1. The right panels depict how promotional effort for drug 2 depends on the discount on drug 1.

promotional effect leads to lower levels of optimal promotional effort regardless of the discounts, we also show that the incentives to shift effort towards the more profitable drug increase with the substitutability between the two products. For example, when drug 2 faces a discount of 50%, drug 1 increases promotional effort as long as its discount is less than 40%.

Panel (c) shows the changes in promotional effort exposure when effort induces positive spillovers in demand.[18] We set $\beta_4 = 2$ and see that optimal promotional effort is highest in the case of positive spillovers, regardless of the discounts. As expected, the firm reduces effort for drug 1 when drug 2 faces a discount, because promotional effort for drug 1 also increases demand for the less profitable drug 2.

The change in prices induced by the 340b price caps has both a direct effect on firm profits through markups and an indirect effect through changes in demand. Hospitals may encourage physicians to switch prescriptions towards drugs with larger discounts, which are more profitable for the hospital. If price caps affect hospital demand for different drugs, this may induce changes in promotional effort in equilibrium. If two firms face different discounts, then the manufacturer of the higher-priced drug may find it optimal to increase its promotional activity to compensate for its price disadvantage from the perspective of the physician (and hospital). That is, both firm competition and optimal promotional effort of a multi-product firm are consistent with our empirical findings. We provide a model of competition that formalizes this intuition in the appendix.

While highly stylized, this model captures the key incentives faced by pharmaceutical firms when determining their advertising strategies under price regulation. Mandated price caps reduce incentives for firms to provide effort. However, differential exposure to discounts across drugs will sometimes entice pharmaceutical firms to shift promotional effort from less profitable drugs to more profitable ones. This incentive will be strongest when there are large disparities in the discounts and when physicians view the drugs in the firm's portfolio as highly substitutable.

6 Heterogeneity in Strategic Responses Across Drugs

6.1 Empirical Strategy

Given the design of the inflation penalties described in Section 2, our model predicts that firm equilibrium responses to the 340b program will vary across drugs. To test this prediction, we estimate versions of Equation (1) and Equation (2) at the hospital-drug level:

$$Payments_{hfdt} = \beta 340b_{ht} + \alpha_{hfd} + \alpha_{tfd} + \varepsilon_{hfdt}, \tag{6}$$

$$Payments_{hfdt} = \sum_{l=-8}^{8} \beta^l D_{ht}^l + \alpha_{hfd} + \alpha_{tfd} + \varepsilon_{hfdt}, \tag{7}$$

where $Payments_{hfdt}$ is the number of payments by pharmaceutical firm f related to drug d received by physicians at hospital h in quarter t, $340b_{ht}$ is an indicator variable equal to one in all quarters in which hospital h participated in the 340b program, and α_{hfd} and α_{tfd} are hospital-drug and time-drug fixed-effects.

[18] Shapiro (2018) identifies positive spillovers of detailing in the context of anti-psychotic drugs.

Table 4: **Effect of 340b Participation on Quarterly Physician Payments, Drug- and Firm-Level**

	Drug-Level	Firm-Level
340b	–0.491***	–0.765***
	(0.0547)	(0.124)
Observations	1,228,963	503,424
Sample Average	2.56	6.10

Notes: Standard errors in parentheses are clustered by hospital-drug for drug-level regressions and hospital-firm for firm-level regressions. Regressions were estimated using Sun and Abraham (2021) to account for staggered treatment timing. We report the average treatment effect on the treated for all treatment cohorts across all treatment periods. * p<0.10, ** p<0.05, *** p<0.01

We examine the potential heterogeneity in responses across drugs by estimating Equation (6) separately for each drug in our "top" drug sample described in Section 3.

We estimate similar models at the firm-level:

$$Payments_{hft} = \beta 340b_{ht} + \alpha_{hf} + \alpha_{tf} + \varepsilon_{hft}, \tag{8}$$

$$Payments_{hft} = \sum_{l=-8}^{8} \beta^{l} D_{ht}^{l} + \alpha_{hf} + \alpha_{tf} + \varepsilon_{hft}, \tag{9}$$

where $Payments_{hft}$ is the number of payments by pharmaceutical firm f received by physicians at hospital h in quarter t, and α_{hf} and α_{tf} are hospital-firm and time-firm fixed-effects.

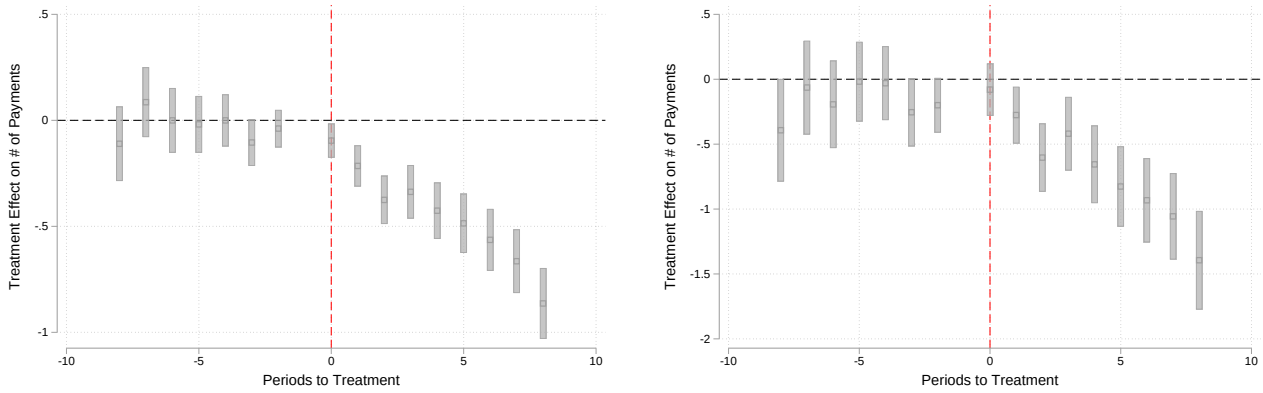
Our primary identifying assumption is that payments for a given drug would follow parallel trends at newly 340b hospitals and control hospitals absent the treatment. The same threats to identification described in Section 4 are present in these drug-level analyses. We acknowledge that we estimate adjustments in promotional effort that are made by firms in equilibrium.

6.2 Results

Table 4 presents the drug- and firm-level regression results from Equation (6) and Equation (8). We detect results that are similar to the aggregated analysis in Section 4: firms make 0.49 fewer payments per drug per quarter to physicians affiliated with newly 340b hospitals relative to physicians affiliated with non-340b hospitals, which corresponds to a 19.1% decrease. Figure 5 presents the analogous event studies from Equation (7) and Equation (9) which again demonstrate that payments were trending similarly at treatment and control hospitals prior to 340b take-up, even within a drug or firm

Next, we describe the heterogeneity in firms' equilibrium responses to the studied price caps across our "top" drug sample. Figure 6 plots the distribution of drug-level treatment effects from Equation (6). While firms reduce promotional payments for many of their drugs, they also increase payments to newly-designated 340b hospitals for some drugs. We highlight drugs with more than 10,000 quarterly promotional payments on average in blue to demonstrate that many of the null effects come from drugs that do not make many promotional payments during our sample period. To better illustrate the magnitude of these estimates, we calculate the percentage adjustment for each drug by dividing each drug-level adjustment by

Figure 5: **Event Study of 340b Participation on Quarterly Physician Payments**



(a) Drug-Level (b) Firm-Level

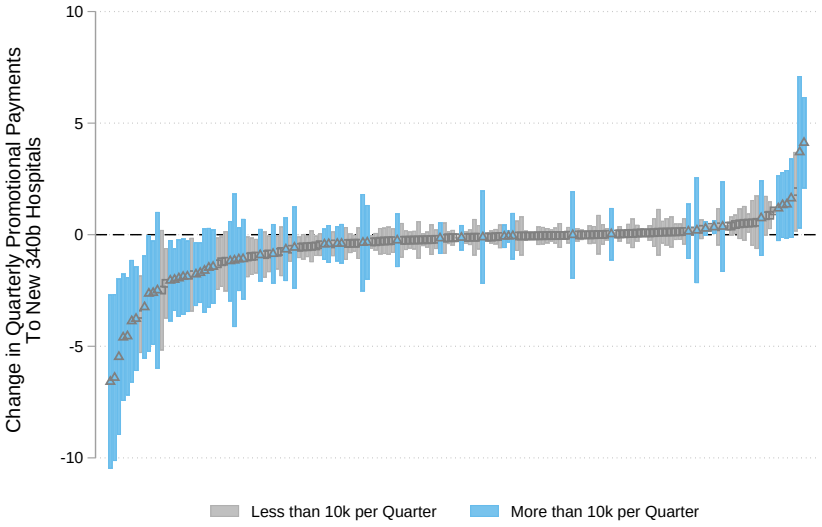
Notes: Standard errors are clustered by hospital-drug or hospital-firm. Drug-level specifications include hospital-drug and year-quarter-drug fixed effects. Firm-level specifications include hospital-firm and year-quarter-firm fixed effects. Regression was estimated using Sun and Abraham (2021) to account for staggered treatment timing. We report the average treatment effect on the treated across all treatment cohorts relative to the quarter before treatment.

its average quarterly promotional payments at the hospital level. Figure 7 presents a histogram of these percentage adjustments in promotional effort, showing again a considerable variation in adjustments around the average of 17%.

In Section 2, we noted that the 340b program should prompt the greatest reductions in promotional effort for older drugs because they are subject to the largest discounts due to the inflation penalty built into the 340b program. In Figure 8, we highlight drugs based on their FDA release date. Consistent with our prediction, the drugs with the largest reductions in promotional payments were all launched before 2015. Importantly, most of the drugs with *increases* in promotional payments to physicians at newly accredited 340b hospitals are new drugs that were launched in 2016 or later.[19]

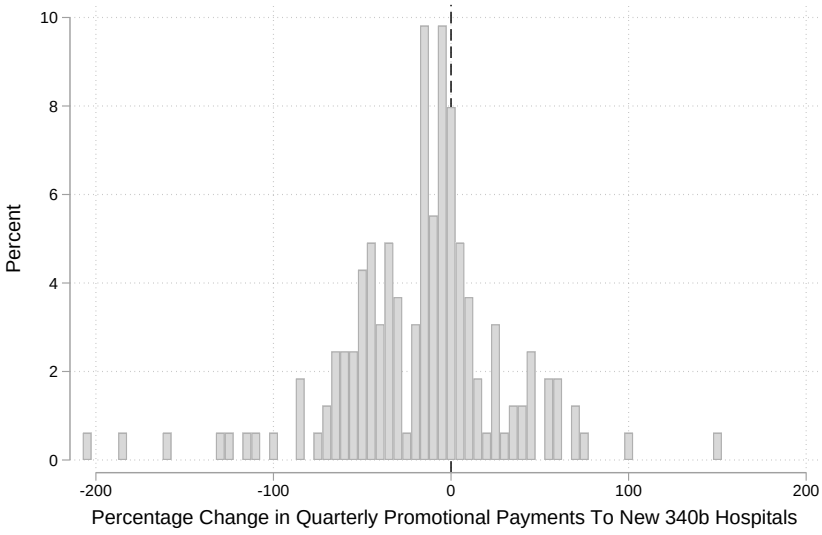
[19] In Figure A.4, we provide the pooled event studies for the three age groups of drugs depicted in this figure to demonstrate that promotional payments for these products were following similar trends at treatment and control hospitals prior to the treatment events that we study.

Figure 6: **Distribution of Drug-Level Treatment Effects**



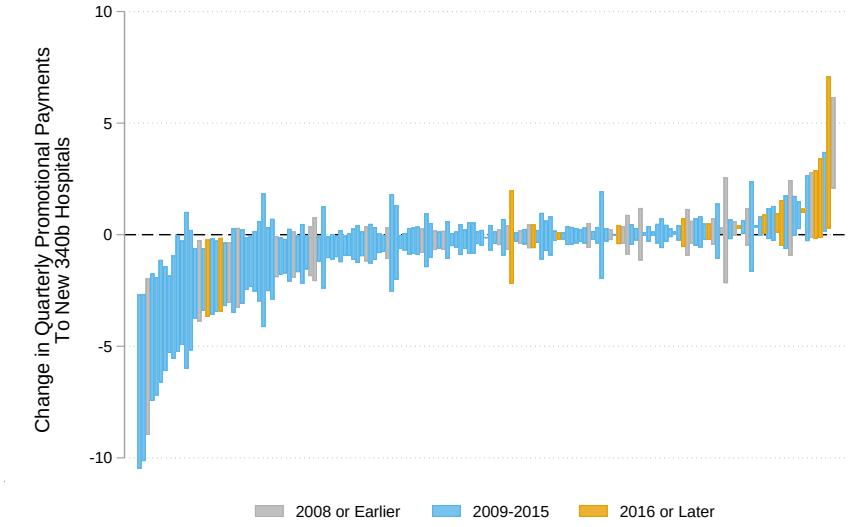
Note: the bars represent 95% confidence intervals.

Figure 7: **Distribution of Drug-Level Treatment Effects in Percentage Terms**



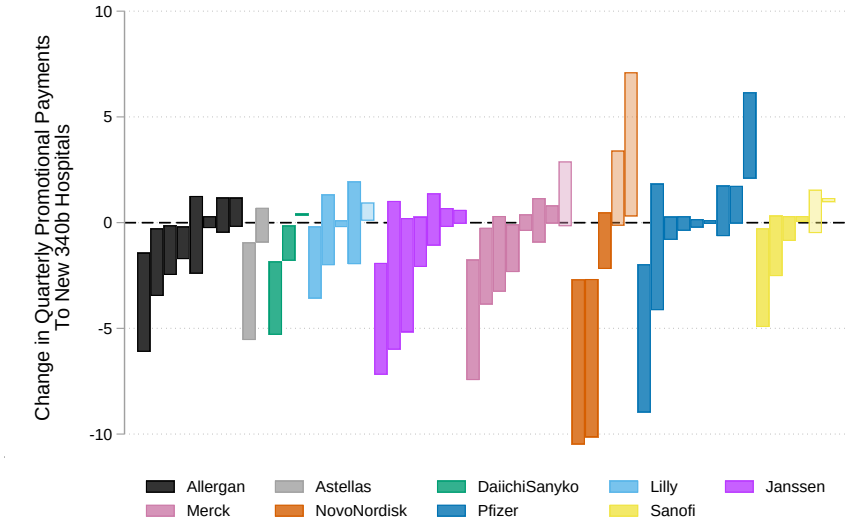
Note: we calculate percentage changes in dividing the estimates from Equation (6) by quarterly average promotional payments per hospital for the given drug.

Figure 8: **Distribution of Drug-Level Treatment Effects, Highlighting by Release Date**



Note: the bars represent 95% confidence intervals. We determine each drug's release date using the FDA NDC Database.

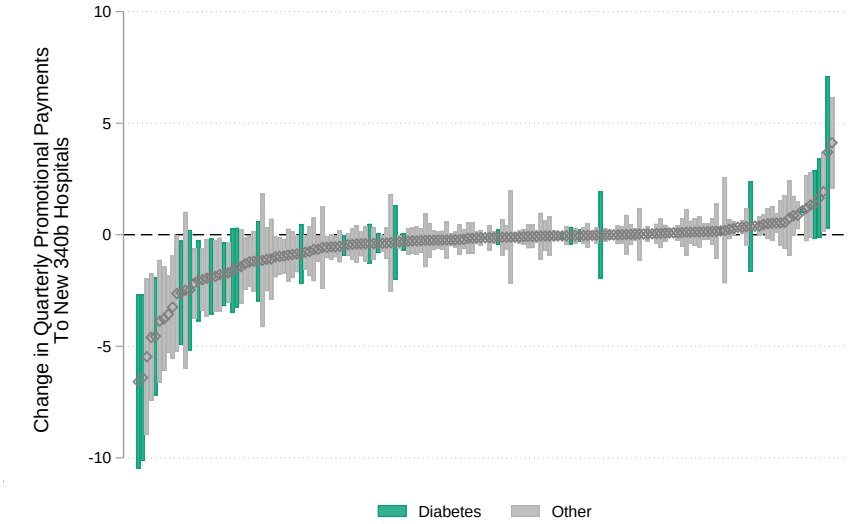
Figure 9: **Within-Firm Heterogeneity by Drug**



Note: the bars represent 95% confidence intervals. Transparent bars represent drugs launched in 2016 or later.

To illustrate the heterogeneous adjustments in promotional effort within a firm across substitute drugs, Figure 9 presents the drug-level estimates grouped by firm for the nine largest pharmaceutical firms. We use transparent bars to identify drugs launched in 2016 and later. Consistent with our earlier findings, pharmaceutical firms typically reduce promotional outreach for most of their products. However, we observe increased promotional payments at 340b hospitals for some drugs, consistent with re-optimization of effort across drugs. We again find that firms shift promotional effort away from older drugs and towards new drugs. While our headline finding that firms reduce promotional effort is consistent with the commonly

Figure 10: **Distribution of Drug-Level Treatment Effects, Highlighting Diabetes Drugs**



Note: the bars represent 95% confidence intervals.

presumed relationship between drug prices and effort, this reallocative effect is the result of variation in the size of the 340b discounts across drugs.

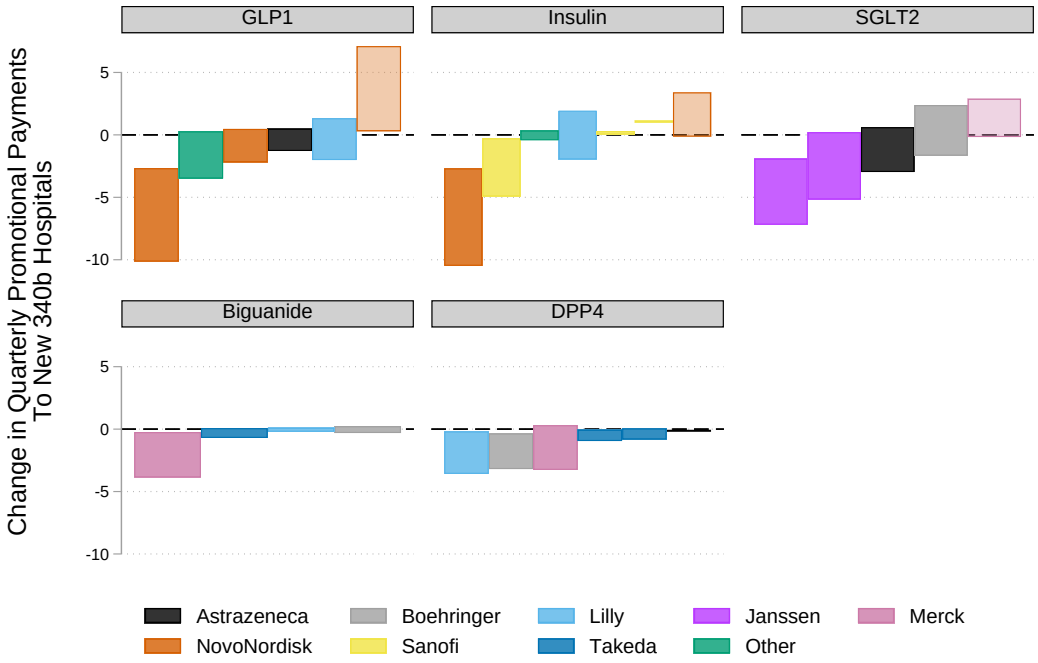
6.3 Case Study of Diabetes Drugs

We use a case study of the diabetes drug market to illustrate the heterogeneous adjustments in promotional effort within a firm across substitute drugs. The diabetes drug market provides a good setting for a case study for at least three reasons. First, diabetes is one of the most common medical conditions in the United States: one in ten Americans have diabetes, and diabetic patients account for 25% of total healthcare spending (American Diabetes Association). Second, diabetes drugs are among the largest advertisers in the OP data: at least 21% of promotional payments are related to diabetes drugs. Finally, we observe large heterogeneity in the response of diabetes drugs to 340b participation. Figure 10 presents the distribution of drug-level treatment effects, highlighting diabetes drugs in green.

We explore adjustments within firms across their set of diabetes drugs and also within more narrowly defined classes of diabetes drugs. We identify drugs that appear in our advertising data for five prominent diabetes drug classes based on online research: biguanides, dipeptidyl peptidase-4 (DPP-4) inhibitors, glucagon-like peptide-1 (GLP-1) receptor agonists, insulin, and sodium-glucose transporter 2 (SGLT-2) inhibitors. This classification allows us to evaluate changes in promotional payments both for close substitutes (i.e., drugs within the same drug class) and for products in different classes. Figure 11 plots the estimated parameters for the diabetes drugs highlighted in Figure 10 separately for each drug class. We color code each drug by its manufacturer and denote newer drugs (i.e., those released in 2016 or later) with transparent coloring.

Within GLP1 and insulin, we see both an increase and a decrease of promotional effort for the same

Figure 11: **Diabetes Drug-Level Treatment Effects by Drug Class**



Note: the bars represent 95% confidence intervals. Drugs were assigned to a treatment category based on online research. Transparent bars represent drugs launched in 2016 or later

pharmaceutical firm that match the prediction of our model. The products with decreased promotional outreach are the older drugs and the products with increases are the newer drugs offered by the same firm. For example, we see that Novo Nordisk reduces payments to physicians at newly 340b hospitals related to Victoza, a GLP-1 approved by the FDA in 2010, but increases payments related to Ozempic, a GLP-1 approved in 2017.[20] Similarly, for insulin, we see that Novo Nordisk and Sanofi (yellow) reduced payments to physicians at newly 340b hospitals related to "legacy" insulins and increased payments related to newly developed insulins, relative to physicians at non-340b hospitals. This re-optimization can also occur across the above definitions of drug classes: for example, Merck (pink) reduced payments related to Janumet (a biguanide launched in 2007) and Januvia (DPP4 launched in 2006), but increased payments for Steglatro (SGLT2 launched in January 2018).

This case study allows us to document strategic reallocation of effort across drugs within a narrowly defined treatment area for which confounding hospital-level changes should have similar effects for firms' promotional strategies. It is unlikely that structural changes at the hospital after the 340b take-up would produce both increases and decreases in effort within the drug class; thus, we attribute this heterogeneity in responses across drugs to differences in discounts set by the 340b program.

[20] Note that our sample period ends in 2019, which was before recent discoveries about Ozempic's potential as a weight-loss product.

7 Conclusion

We study how price regulations affect the decisions of pharmaceutical firms to provide promotional effort. We measure effort using publicly disclosed promotional payments to physicians, which represent a measurable and locally determined unit of effort that is likely to respond to changes in markups. We exploit changes in participation by hospitals in the 340b drug pricing program to understand how firms adjust their provision of in-kind promotional payments in response to changes in price.

We provide evidence that pharmaceutical firms respond strategically to the design of the 340b program price caps. The program induces pharmaceutical firms to reduce overall promotional payments, consistent with commonly-held views about the relationship between prices and advertising. However, we show that pharmaceutical firms increase promotional effort for drugs facing less severe government-imposed price caps. These unexpected increases can be explained by either the portfolio management incentives of multi-product firms, who may use physician marketing to reduce their exposure to price caps that vary across products. In sum, our analysis highlights the complexity of the relationship between prices and advertising.

In-kind transfers to physicians are an important, but often contentious, form of pharmaceutical promotion. While in-kind transfers offer physicians an opportunity to learn new information about drugs, they may also lead to overprescribing (Alpert et al. (2022)). While this paper does not assess the welfare effects of changes in promotional effort due to the lack of data on observed health outcomes, we offer some brief speculation on the likely welfare impact of the changes in promotional effort that we observe, given that firms adjusted promotional effort away from older drugs and towards younger drugs. Specifically, if promotional payments for younger drugs are more likely to provide physicians with new information compared to payments for older products, or if they are more likely to accelerate the adoption of superior drugs, then the 340b program may have (possibly unintentionally) incentivized firms to engage in promotional activities that are on average more socially beneficial.[21]

Our analysis also offers insights into the effects of other regulations in the pharmaceutical industry, such as the drug pricing provisions of the Inflation Reduction Act (IRA). The design of the IRA price regulations contains provisions that are similar to the 340b program. Specifically, the IRA empowers the federal government to negotiate rebates in Medicare, but small-molecule drugs that have been on the market for less than nine years are excluded from this negotiation, and the IRA implements an inflation penalty similar to the 340b additional rebate (Cubanski et al. (2023)). As a result, the IRA will reduce markups mostly for older drugs, with less of an impact on drugs in their first few years on the market. This design feature generates similar incentives as the 340b program discounts. Based on our analysis, we would expect pharmaceutical firms to reduce promotional outreach for older drugs that are subject to the "negotiations" clause of the IRA and potentially increase outreach for some newer drugs in order to reduce their exposure to the IRA.

[21] Chambers et al. (2017) finds that the median drug approved by the FDA between 1999 and 2012 produced gains over existing treatments, as measured using quality-adjusted life years.

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Data Appendix

Our main dataset is the Open Payments (OP) data for 2014-2019. We focus on meal payments, as identified by the "Nature of Payment" variable. For each payment, the OP data lists the firm that made the payment, the date of the payment, the NPI number of the doctor who received the payment, and the products associated with the payment, including a classification of the product (drug, biologic, device, or medical supply) and the product's National Drug Code (NDC), where applicable. We use the broad product classifications to identify devices and supplies for our placebo analysis. For each payment, there can be up to five products associated with the event. For our hospital- and firm-level analyses, we count each payment only once, regardless of how many drugs were discussed during the visit. For our drug-level analyses, we count each payment once for every drug discussed during the visit.[22] We assume that pharmaceutical and medical device firms abide by the OpenPayments law and accurately report all required information to CMS.

We link the OP data to the National Drug Code (NDC) database provided by the US Food and Drug Administration (FDA) to obtain more detailed information about drugs. Because the NDC database does not include information on discontinued drugs or discontinued packages of drugs, we obtain this information for some drugs using historical versions of the NDC databases from 2016-2019 using the Wayback Machine. We use the most current information available for each NDC. The dataset contains information on the drug's product type (e.g., vaccine) and its marketing start date. We link databases by the 11 or 10 digit NDC package code, or by 9 digit product code if the package code from OP was not listed in the FDA data. We made some additional merges by manually matching drugs in the OP data to the FDA data when possible. We manually standardized names for the firms and drugs that we include in our sample for all analyses at the firm- and drug-level. In doing so, we aggregate payments for the same drug across different NDCs, which represent different package sizes or formulations of the same treatment. We use the "Product Type Name" field in the NDC database to identify payments related to vaccines, which are not covered under the 340b program, because the classifications in the OP data do not separately identify vaccines.

We use the NDC database to obtain the marketing start date for each drug. A drug's marketing start date is the date that the product entered commercial distribution. A drug may have multiple marketing start dates across NDCs, most likely due to reformulations or different packages of the same product. For each drug, we assign it the earliest start year of any NDC observed in both the OP and FDA data, conditional on at least one percent of that drug's payments in the OP being for NDCs with that start year. We manually checked that the marketing start dates for each drug were accurate and made corrections when necessary.

We define the universe of active physicians in each year as the doctors who appear in the National Downloadable File (NDF) data. These data contain the set of physician who received any reimbursements from Medicare in that year. In the empirical analyses, we use payments for which the physician/year combination appeared in the NDF data. 65% of physician-year combinations have at least one hospital affiliation listed in the National Downloadable File. For physicians with multiple hospital affiliations, we treat the first listed hospital for each professional as their primary hospital affiliation (which we understand to be the norm per

[22] For example, if a firm lists drug A and drug B as being discussed during a given meal, we count that payment once towards drug A and once towards drug B.

correspondence with CMS).[23] We link the OP and NDF datasets by National Provider ID (NPI) using the Physician Profile Supplement data provided along with the OP data.

We link the NDF to CMS hospital-level datasets using the CMS Certification Number (CCN), which uniquely identifies hospitals. We restrict the sample of hospitals to those that appear in the HCRIS data in every year 2014-2019 in order to avoid detecting changes in advertisements due to closures.[24] The empirical analyses focus on short-term general acute care (GAC) hospitals. We exclude critical-access hospitals, which serve remote areas and are automatically eligible for the 340b program. We also exclude specialty hospitals that are also eligible for the 340b program (cancer and children's hospitals), and hospitals for which the facility type indicated it was reserved for demonstration projects. Hospitals in the same system may sometimes report to CMS under independent hospital IDs and other times report together under a single ID. We drop one treatment hospital (330214 - NYU Langone Hospitals) that began reporting jointly with other hospitals in the same system at the same time as 340b take-up, because we are unable to assign physicians to different facilities within the same system when the hospitals report together. Finally, our analysis excludes hospitals located in US territories.[25]

We manually calculated DSH %'s for each hospital-year, because the DSH % reported by hospitals are capped at 12% for many hospitals.[26] Hospitals report their annual Disproportionate Patient Percentage (DPP), which is the sum of Medicare Supplemental Security Income Days (divided by Total Medicare Days) and Medicaid, Non-Medicare Days (divided by Total Patient Days). The formula for the DSH that is set by CMS is non-linear. A hospital's DSH % is calculated as $2.5\% + 0.65 * (DPP - 15\%)$ until it reaches 12%, after which it is calculated as $5.88\% + (0.825 * (DPP - 20.2\%))$. We use this re-constructed DSH % for some of our descriptive analyses and to identify hospitals that had at some point been eligible for the 340b program, which we use to define the control group for our empirical analyses.

To identify the hospitals who participate in the 340b program, we rely on publicly available data from the Health Resources and Services Administration (HRSA) Office of Pharmacy Affairs Information System. The HRSA data contain detailed information on 340b program participants (commonly referred to as "covered entities"), including information on the dates that they participated. Covered entities include hospitals as well as any affiliated outpatient clinics that participate in the program.[27] For each covered entity, the HRSA data lists its "registration date", "participating start date", "participating approval date", and "last recertification date." We noticed that HRSA frequently overwrites these fields in a manner that made it difficult to ascertain the participation histories of hospitals from snapshot extracts of the HRSA data. As a result, we manually reviewed the history of profile adjustments maintained by the HRSA for each hospital, which allowed us to more accurately determine the dates that each hospital participated in the 340b program.

[23] We are unable to track movements by physicians across hospitals within a given year using the National Downloadable File. It is also possible that the hospital affiliation in these data do not fully capture financial affiliations between outpatient physicians and hospitals. Nevertheless, we believe the National Downloadable File affiliations to be mostly reliable, particularly for physicians who practice in a hospital-owned facility, which are most likely to be affected by the 340b program.

[24] We thank Adam Sacarny for providing his code to clean the HCRIS data (Sacarny (2022)).

[25] This includes the Virgin Islands, Puerto Rico, Mariana Islands, Guam, and American Samoa.

[26] The primary function of reporting the DSH % is to determine Medicare DSH Adjustments, which compensate hospitals for serving a significantly disproportionate number of low-income patients. This DSH payment is capped at 12% for most hospitals.

[27] For example, there are separate entries for "University of Virginia Medical Center" and "University of Virginia Medical Center Outpatient Surgery Center - 2660."

Some covered entities start and stop participating in the 340b program during the time period. We define a hospital as participating in the program in a given quarter if the hospital or any of its affiliated outpatient clinics were participating in the program. We define a hospital as a treatment hospital if it took up the program between 2016q1-2018q1 and had not been previously participating, and remained in the program through the end of 2019 with no lapses in participation. Our control hospitals are hospitals that did not participate in the 340b program at any point during 2014-2019 but were at some point eligible for the program (e.g., "never-treated" hospitals). We consider alternative control group definitions in the appendix. We exclude two types of hospitals from our analysis: "always-treated" hospitals that were in the program for all of 2014-2019, and "sometimes-treated" hospitals that change 340b status more than once during 2014-2019. 890 hospitals are always-treated, and 228 hospitals are sometimes-treated. Of these 228 sometimes-treated hospitals, 20 hospitals were not participating in the program at the beginning of the sample and were participating at the end of the sample, but experienced at least one lapse in participation. Because it is unclear what triggered these lapses or how pharmaceutical firms would respond to these lapses, we exclude these hospitals entirely from our empirical analyses.

Appendix Tables & Figures

Table A.1 presents summary statistics separately for three sets of the hospitals: the 115 hospitals that comprise our treatment group; the 267 hospitals in our control group; and the 890 always treated hospitals, for comparison.

Table A.1: **Hospital-Level Summary Statistics, 2014q1**

	(1) Treatment		(2) Control		(3) Always-Treated	
	Mean	SD	Mean	SD	Mean	SD
# of Professionals	237.91	283.68	98.28	150.93	258.49	278.55
# of Beds	246.44	283.26	104.40	128.90	283.96	248.78
# of Part D Prescriptions per Professional	3835.88	3422.18	3503.97	2502.61	3109.76	1722.96
# of Detailing Payments per Professional - Drugs	2.87	2.07	2.35	2.16	2.52	1.84
# of Detailing Payments per Professional - Device	0.43	0.28	0.35	0.47	0.41	0.28
$ of Detailing Payments per Professional - Drugs	49.20	31.88	40.35	35.41	45.77	31.56
$ of Detailing Payments per Professional - Device	17.99	13.04	14.04	20.39	17.22	13.00
DSH %	0.15	0.41	0.14	0.16	0.23	0.13
Rural Hospital	0.30	0.46	0.41	0.49	0.31	0.46
Observations	115		267		890	

Table A.2 presents estimates of Equation (1) where we exclude control hospitals if they are in the same hospital referral region (HRR) as a treatment group hospital. We detect slightly more negative effects on drug payments, consistent with negative spillovers on promotional payments at hospitals that are more distant from 340b hospitals. Our detected placebo effect on promotional payments for medical devices and supplies is virtually unchanged.

Table A.3 presents estimates of Equation (1), Equation (6), and Equation (8) where we remove the requirement that control hospitals must be eligible for the 340b program in at least one quarter. In all specifications, we exclude control hospitals that are located in the same HSA as one of our treatment group hospitals. The results are qualitatively similar.

Table A.2: **Effect of 340b Participation on Quarterly Physician Payments, Hospital-Level Sensitivity to Spillovers**

	Drugs		Medical Devices + Supplies	
	(1)	(2)	(3)	(4)
340b	–46.7***	–50.2***	2.47	3.07
	(16.4)	(16.8)	(3.07)	(3.23)
Treatment Group	Any Hospitals	Any Hospitals	Any Hospitals	Any Hospitals
Control Group	Ever Eligible Hospitals, Not In Same HSA As Treatment Hospital	Ever Eligible Hospitals, Not In Same HRR As Treatment Hospital	Ever Eligible Hospitals, Not In Same HSA As Treatment Hospital	Ever Eligible Hospitals, Not In Same HRR As Treatment Hospital
Observations	9,168	7,104	9,168	7,104
Sample Average	354	376	64.3	69.8

Notes: Standard errors in parentheses are clustered by hospital. Regressions were estimated using Sun and Abraham (2021) to account for staggered treatment timing. We report the average treatment effect on the treated for all treatment cohorts across all treatment periods. * p<0.10, ** p<0.05, *** p<0.01

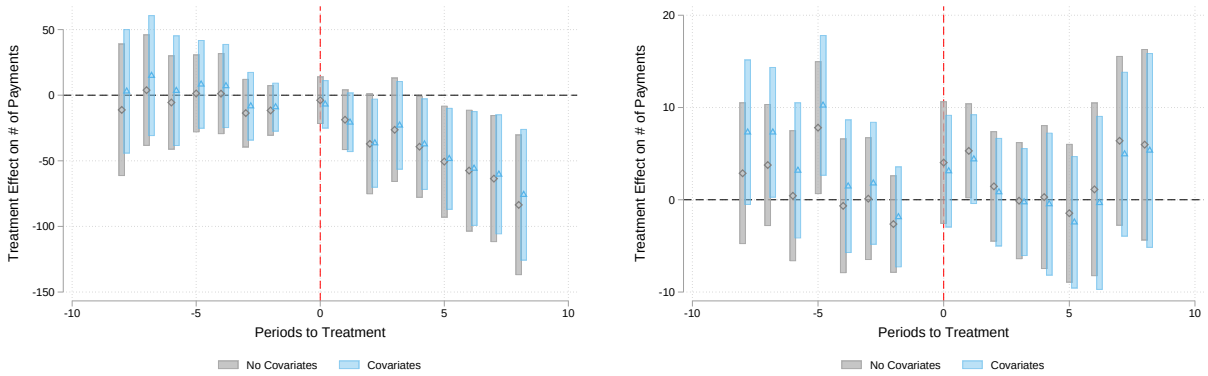
Table A.3: **Robustness to Alternative Control Group Definitions**

	Hospital Level		Drug-Level		Firm-Level	
	(1)	(2)	(3)	(4)	(5)	(6)
340b	–46.7***	–33.1**	–0.491***	–0.320***	–0.765***	–0.568***
	(16.4)	(15.5)	(0.0547)	(0.0519)	(0.124)	(0.117)
Treatment Group	Any Hospitals	Any Hospitals	Any Hospitals	Any Hospitals	Any Hospitals	Any Hospitals
Control Group	Ever Eligible Hospitals	Any Hospitals	Ever Eligible Hospitals	Any Hospitals	Ever Eligible Hospitals	Any Hospitals
Observations	9,168	38,232	1,228,963	5,422,375	503,424	2,225,910
Sample Average	354	426	2.56	2.90	6.10	6.89

Notes: Standard errors in parentheses are clustered by hospital. Regression was estimated using Sun and Abraham (2021) to account for staggered treatment timing. In all specifications, we exclude control hospitals that were in the same HSA as a treatment group hospital. We report the average treatment effect on the treated for all treatment cohorts across all treatment periods. * p<0.10, ** p<0.05, *** p<0.01

Figure A.1 estimates Equation (2) with time-varying hospital covariates. We interpret these results as suggestive evidence that the take-up of the 340b program was not correlated with important unobserved changes at the hospital that would affect physician payments separately from the 340b discounts.

Figure A.1: **Hospital-Level Event Study, Robustness to Time-Varying Hospital Covariates**



(a) Drugs (b) Medical Devices and Supplies

Notes: Standard errors are clustered by hospital. All specifications include hospital and year-quarter fixed effects. Regression was estimated using Sun and Abraham (2021) to account for staggered treatment timing. The blue bars control for lagged DSH %, total beds, and number of medical professionals, which vary by hospital and year.

Figure A.2 shows the results when we use a synthetic control approach that allows us to compare newly accredited 340b hospitals to control hospitals with similar characteristics. For each treated hospital, we construct a synthetic control hospital from the set of never-treated hospitals (excluding hospitals in the same HSA as one of our 115 treatment hospitals) by matching on pre-treatment quarterly promotional drug payments, DSH %, number of beds, and number of medical professionals.[28] We stack this equation for treated hospital i,

$$Payments_{it} = \beta 340b_{it} + \alpha_i + \alpha_{it} + \varepsilon_{ist}, \tag{10}$$

with the analogous equation for the synthetic control i',

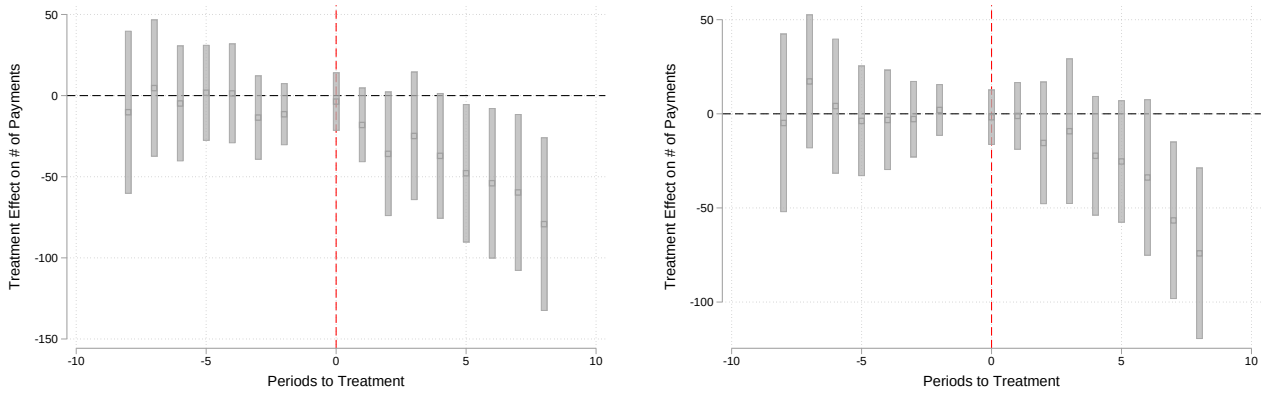
$$Payments_{i't} = \alpha_{i'} + \alpha_{it} + \varepsilon_{i'st}. \tag{11}$$

We allow separate fixed effects for each hospital i and synthetic hospital i', but include hospital-time fixed effects it, such that we are essentially "stacking" separate within-hospital experiments for each treatment hospital. We pool these equations across treated hospitals and estimate using the Sun and Abraham estimator to account for staggered timing of treatment. Figure A.2 provides the results from our synthetic control methodology alongside our main estimates from the draft. The results are roughly similar. This provides some reassurance that selection on observable characteristics does not drive our main results.

Figure A.3 presents the estimates from Equation (8), separately for each of our top pharmaceutical firms. The distribution closely resembles the distribution in Figure 6. We highlight firms that made at least ten thousand payments per quarter in blue to demonstrate that many of the null effects are connected to pharmaceutical firms that do not make very many physician payments.

[28] We match on the pre-treatment averages for all of these variables.

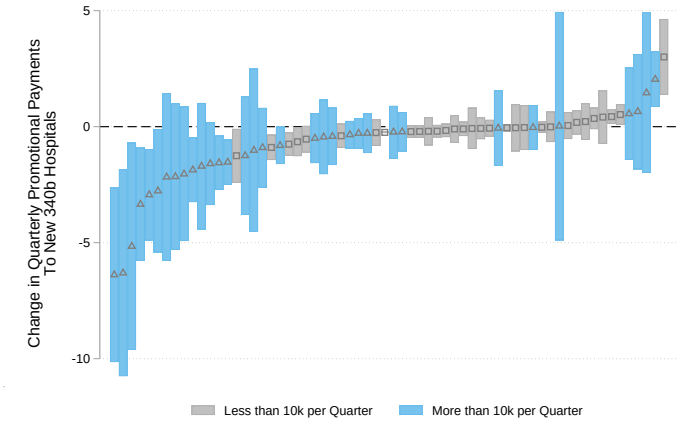
Figure A.2: **Event Study of 340b Participation on Quarterly Physician Payments, Hospital-Level, Synthetic Control Methodology**



(a) Main Version (b) Synthetic Control

Notes: Standard errors are clustered by hospital. All specifications include hospital and year-quarter fixed effects. We report the average treatment effect on the treated across all treatment cohorts relative to the quarter before treatment.

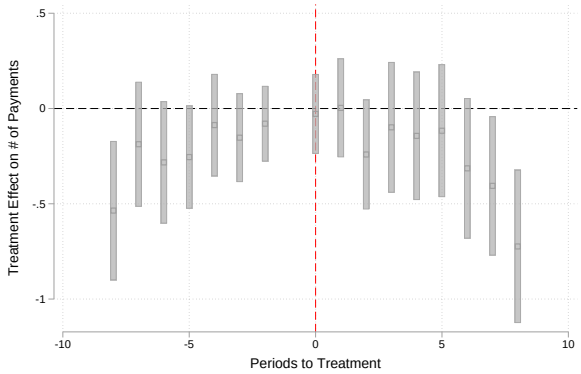
Figure A.3: **Distribution of Firm-Level Treatment Effects**



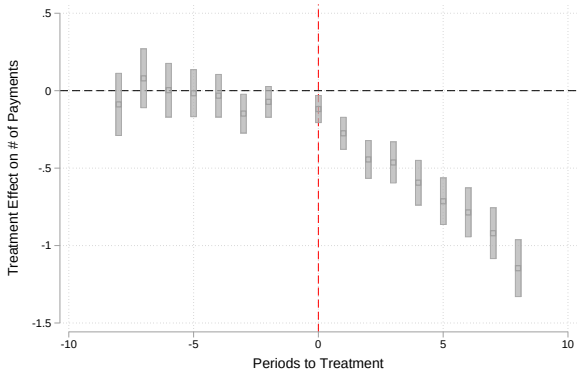
Note: the bars represent 95% confidence intervals.

Figure A.4 presents the estimates from Equation (6), separately for each of the three drug age categories used in Figure 8. These event studies demonstrate that our drug-level results do not appear to be driven by secular trends in promotional payments.

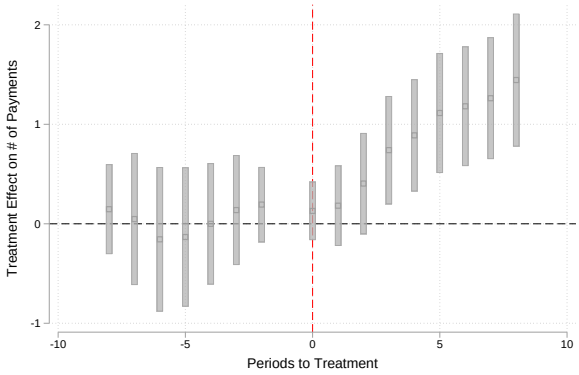
Figure A.4: **Drug-Level Event Studies, Separately by FDA Approval Date Range**



(a) Approved Before 2008



(b) Approved Between 2008-2015



(c) Approved in 2016 or Later

Notes: Standard errors are clustered by hospital-drug. All specifications include hospital-drug and year-quarter-drug fixed effects. Regression was estimated using Sun and Abraham (2021) to account for staggered treatment timing.

A Model of Competition and Promotion

In Section 5, we showed how price caps can induce a multi-product monopolist to increase promotional effort for some drugs. In this appendix, we demonstrate how they can also induce competing firms to increase promotional effort. We consider competing duopolists who sell differentiated drugs that treat the same condition. We assume that a given physician i receives utility from prescribing drug j according to

$$u_{ij} = \gamma_j + \beta_1 p_j + \beta_2 log(a_j) + \varepsilon_{ij}, \tag{12}$$

where ε_{ij} is distributed type 1 extreme value.[29] The outside option for the physician is to not prescribe a drug and receive utility $u_{i0} = \varepsilon_{i0}$. Given the assumption on the distribution of ε_{ij}, we can write the market share for drug j as

$$s_j = \frac{exp(u_j)}{1 + \sum_j exp(u_j)}. \tag{13}$$

Profits for firm j can thus be written as

$$\Pi_j(\mathbf{p}, \mathbf{a}) = s_j(\mathbf{p}, \mathbf{a})(p_j - c) - w * a_j, \tag{14}$$

Maximizing profits with respect to a_j provides the first order conditions that determine equilibrium levels of promotional effort:

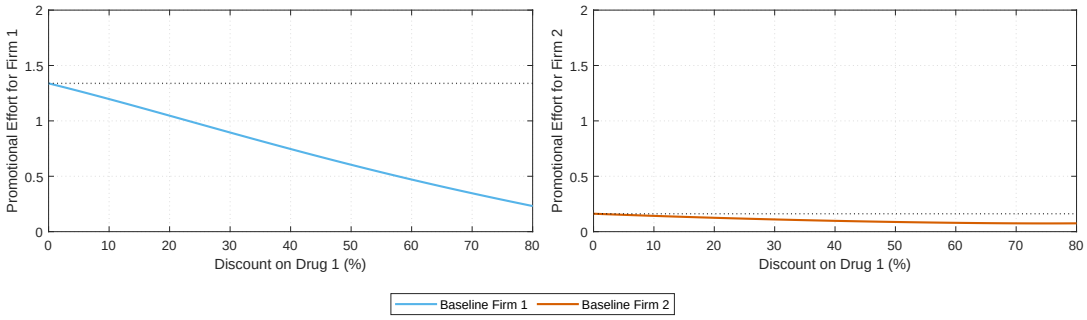
$$\frac{\beta_2 s_j(1 - s_j)}{a_j}(p_j - c) = w. \tag{15}$$

Firms reduce promotional effort in response to caps on the prices of their own drugs, captured by the left-hand side of Equation (15). The strategic response to a change in the price of *rival* drugs is less clear because promotional effort responds to both (i) the change in the rival's price, and (ii) the change in a rival's promotional effort induced by the price change.

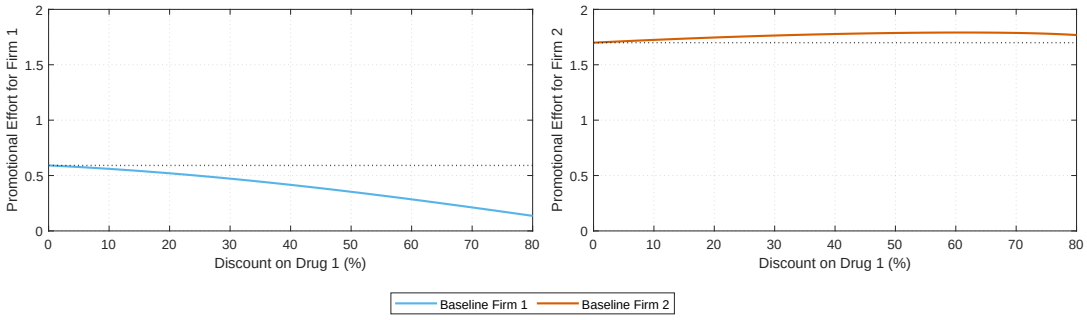
Figure A.5 presents two numerical simulations in which we plot how each firm would adjust promotional effort in response to a price cap faced by firm 1. These simulations show that competition between firms can also cause the same responses that we observe in the data under certain parametric assumptions. We see that under some parameter values, firm 2 reduces promotional effort in response to discounts on firm 1's drug, while under others parameter values, firm 2 increases effort.

[29] While the linear demand from Section 5 was helpful for illustrating multi-product firm incentives, we switch to this logit utility function because it allows for a firm's promotional decisions to depend on its rival's price.

Figure A.5: **Competition Model Simulation**



(a) $\gamma_1 = 2, \gamma_2 = 0$



(b) $\gamma_1 = 2, \gamma_2 = 4$

Notes: we set $\beta_1 = 0.75$, $\beta_2 = 0.5$, $w = 0.25$, and $c = 0$ for these simulations. We hold prices fixed at the profit-maximizing prices for both firms when there are no discounts.