The Causal Effects of Pharmaceutical Payments on Physician Prescriptions

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JOB MARKET PAPER

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*Department of Economics, University of Rochester. Email: alonbergman@gmail.com. I am indebted to my advisors Ronni Pavan and Gregorio Caetano for their guidance and support, and to Carolina Caetano and Nese Yildiz for their generous help and advice. Additional thanks to participants in seminars at the University of Rochester. All errors are my own.

1 Introduction

US expenditures on pharmaceuticals have increased by 67 percent from 2000 to 2015, and amounted to 2.1 percent of the GDP in 2015. During the same period, pharmaceutical industry expenditures on detailing (marketing to physicians) have increased at a similar rate (Dingus, 2014). The majority of pharma promotions are directed at physicians; of the $15.6B the top 20 pharmaceutical firms spent on promotions in 2015, only 25 percent were directed at consumers (MM&M, 2015). The role and effect of detailing activity, and the payments often associated with it (lunches, gifts, educational material) are under heated debate. Proponents of detailing state that it "ensures timely access to new studies, clinical data, dosing information, and updated drug safety profiles" (Pharmaceutical Research and Manufacturers of America, 2008) while the World Heath Organization raised concerns of "an inherent conflict of interest" between pharma and physicians' goals.[1] Yet identifying the causal effects of detailing and payments on physician prescribing is confounded by the inherent endogeneity: physicians are targeted in a nonrandom way into detailing and payments by pharmaceutical companies.

This paper estimates the causal effects of physician payments on physician prescribing behavior. I employ a novel identification strategy, examining the behavioral changes of physicians who stopped receiving drug-related payments due to changes to drug producer ownership, which are exogenous to any physician-specific unobservable. I use this identification strategy to estimate the effects of drug-related payments on physicians prescribing to Medicare Part D beneficiaries in 2013-2015, focusing primarily on a class of drugs intended to treat inflammatory bowel disease.

Previous papers have attempted to identify the causal effects of detailing on physician prescribing by controlling for physician fixed-effects. More recently, Shapiro (2017) studies the effect of detailing for the anti-psychotic drug Seroquel, concluding that the positive effect of detailing cannot be attributed to informational shocks relating to the molecule. Carey et al. (2017) study the effects of payments on Medicare Part D prescribers, finding

[1] "An inherent conflict of interest between legitimate business goals of manufacturers and the social, medical and economic needs of providers and the public to select and use drugs in the most rational way." (World Health Organization, 1993)

that detailed physicians prescribe higher-quality brands on average, and interpret this as evidence of information transfer associated with payments.

This paper provide evidence showing that physician fixed-effects do not resolve the bias generated by selection into payments, and are not sufficient for identifying these causal effects. Pharmaceutical companies assign physicians in and out of detailing schedule based on time-varying characteristics of physicians, which are not absorbed by atemporal physician fixed effects. My results suggest that physicians who respond to payments by increasing molecule prescriptions are less likely to be contacted again.[2] These empirical results are supported by anecdotal evidence: In one leading pharmaceutical company, detailing targets were determined yearly, adjusted quarterly, and varied monthly based on other factors (Manchanda et al., 2004). My own interviews with a pharmaceutical sales manager at a top five pharmaceutical company suggests detailing assignment is adjusted based on a rolling four-week analysis of the physician's prescribing trends.

I use a novel identification strategy to identify and estimate the causal effects of drug-related payments to physicians on the latter's prescribing habits. I examine drugs that change ownership, either by company acquisition or the acquisition of drug patent rights. I show that changes in drug ownership are often followed by a drastic change to drug marketing schemes, including changes to the set of physicians who receive drug-related payments. My identifying assumption is that cessation in drug payments to physicians following a drug acquisition is uncorrelated with physician unobservables, if the cessation occurs to all or nearly all paid physicians.

I obtain data on pharmaceutical payments to physicians from the Open Payments dataset. To the best of my knowledge, this is the first paper in economics literature to make use of this public-use resource, which contains detailed information on all payments given to physicians from pharmaceutical and medical device manufacturers from 2013Q3 to 2016Q4 (latest release as of date). I match physicians from the Open Payments dataset to the public-use Medicare Part D data to generate a dataset of physician prescribing and pharmaceutical payments spanning the years 2013 through 2015.

[2]Similarly, Manchanda et al. (2004) find that physicians who are less responsive to detailing are detailed more than responsive physicians.

This identification strategy can be used to study the effects of payments and detailing for many different brands and drug classes. The pharmaceutical industry is characterized by dynamic and rapid acquisitions and mergers, with over 49 pharmaceutical companies with approved brands who were acquired in 2014-15, and a similar number of pharma with products still in development (Vitez and Harrison, 2016). Focusing on acquisitions that occurred in later 2013 through early 2015, I identify over 18 firms whose drugs are prescribed in Medicare Part D. For 8 of these firms, I observe a sharp change in payments given to physicians around the time of acquisition.

I showcase my identification strategy on the aminosalicylate drug class, a group of agents used to treat inflammatory bowel disease (IBD). An estimated 3.1 million, or 3.1 percent of U.S. adults have received diagnosis of IBD, a spectrum of chronic inflammatory intestinal conditions chiefly composed of Crohn's disease and ulcerative colitis (Dahlhamer et al., 2016). Though rarely fatal, pain, malnutrition and complications can reduce quality of life for patients with IBD. Furthermore, the condition has no cure; the purpose of drug treatment is to induce and maintain disease remission.

I focus on aminosalicylates for several reasons: First, it is the mainstay drug class for treating IBD, both in inducing disease remission and maintaining it (Burger and Travis, 2011). Second, it is a competitive drug class, with three generics and seven brands, six of which are associated with payments to physicians. Third and most importantly, four of the class brands (Asacol HD, Delzicol, Canasa and Apriso) were owned by firms that underwent acquisition during the period for which I have data, enabling me to apply my identification strategy to multiple brands within a single class of drugs.

I perform a Difference-in-Difference analysis, analyzing the behavior of physicians who stop receiving brand-related payments due to firm acquisition, while controlling for the national prescription trends of those brands. Observationally, physicians who are targeted for payments prescribe more aminosalicylates than other physicians. I find that stopping payments related to a specific brand has a causal class-shrinking effect on physician prescribing habits. Physicians who stopped receiving payments related to aminosalicylate brands were less likely to continue prescribing aminosalicylates of any kind in the years following payment cessation. The probability reduction is measured at 3.3-5.4 percentage

points one year after cessation, and 6.5-9.2 percentage points two years after cessation, with some variation across brands. I find no evidence that these physicians are shifting to other drug classes used in treating IBD.

Much of the research into detailing effects has focused on the two hypothesized roles of detailing; persuasive and informative. Some evidence of the aggregate effects of detailing led it to be interpreted as persuasive (Leffler, 1981; Hurwitz and Caves, 1988; Rizzo, 1999). A recent literature has attempted to empirically decompose the two effects. Narayanan and Manchanda (2009) identify information and persuasion by function form assumptions, where information affects belief about drug efficacy, while persuasion enters the physician's utility directly. They conclude that the persuasive effect accounts for 35-41 percent of detailing effects. Ching and Ishihara (2012) use comarketing agreements, where several drug producers market the same molecule under different brands, to identify the different roles of detailing. Their identifying assumption is that brand-specific effects are persuasive, while molecule-specific effects informative, finding that the informative effect is mainly responsible for molecule level demand, while the persuasive effect dominates brand level demand.

I suggest a closely-related decomposition. I separate payment treatment effects to permanent and transitory components.[3] I derive an upper bound for the size of the permanent effect of payments on prescribing. I find that payments have a more transitory effect on brand preference, and a more permanent effect on the decision to prescribe any aminosalicylate therapy. I find that at least 29 percent of the effect of payments on the decision to prescribe aminosalicylate is transient in nature, decaying completely within two years after payment cessation.

Lastly, I estimate a discrete choice model of physician prescription. The purpose of the model is trifold. First, to fit my results in the common framework in the literature, which is set at the physician-patient level. Second, to interpret my results with respect to the outside option (not prescribing drug therapy). Third, to generate counterfactuals

[3]In Narayanan and Manchanda (2009); Ching and Ishihara (2012) persuasive effects are considered transitory, and modeled as a decaying *goodwill* stock. In Narayanan and Manchanda (2009) informative detailing make physicians update their belief about the true drug quality, and are persistent.

that allow for flexible brand substitution patterns. As I do not observe patient level data, I employ an aggregate logit model, similar to the methodology developed by Berry et al. (1995). I consider the counterfactual in which payments for brands did not cease as a result of acquisitions, and estimate that a total of 2140 months of aminosalicylate therapy would be prescribed in 2015, a national increase of 0.6 percent. The total cost of these additional prescriptions is estimated at $943,000.

This paper makes three contributions. First, it provides empirical evidence showing that physician fixed effects are not sufficient for recovering causal effects of payments and detailing on physician prescriptions. Second, it provides causal estimates of pharmaceutical payment effects on physician prescribing, using a novel identification strategy that can be applied to numerous drug classes. Third, it provides empirical evidence suggesting that payments have class-expanding effects, and that these are at least partially temporary.

The paper is organized as follows. Section 2 describes my data and the empirical setting of the aminosalicylate market. Section 3 describes the methodology. Section 4 contains the main results and sensitivity analyses. Section 5 details the physician prescription model, and estimates and counterfactual generated from it. Section 6 concludes.

2 Data and Empirical Setting

I construct my dataset from two publicly available sources of data. I use prescription data for all Part D physicians for 2013 through 2015 from the Centers of Medicare and Medicaid Services (CMS). I merge this data with 2013Q3-2015Q4 pharmaceutical payments data from the Open Payments dataset, which details payments from drug and device products to all US physicians. Doing so, I generate a unified dataset linking physician prescribing of specific drugs to payments received for these drugs, and the producing pharmaceutical company. To the extent of my knowledge, this paper is the first to utilize these datasets, whether separably or jointly, in economic research.

2.1 Prescription Data

I use prescription data from all Medicare Part D physicians in 2013-2015 from the "Medicare Provider Utilization and Payment Data: Part D Prescriber" dataset. This public use data is made available by CMS. The data files contain information on all prescription drug payments associated with Medicare Part D in the years covered. The data is aggregated to the {physician,drug,year} level, and includes information on claim counts, beneficiary counts and total drug costs. One limitation of the data is truncation, as physician prescribed drugs with fewer than 11 claims are not included in the sample.

Physicians are identified by their National Provider Identifier (NPI). Drugs are identified by brand name (if a brand is dispensed) and the generic name of the drug's molecule or compound. The dataset only details the drugs actually dispensed to beneficiaries, rather than the drugs prescribed - this is important to note, as pharmacies may substitute prescribed drugs (for example, by substituting a prescribed brand with a cheaper generic alternative). The dataset also contains information on the demographic composition of the physician's part D beneficiaries, including average age of beneficiary, as well as counts of beneficiaries by age group, by race, and by sex.

I restrict my sample of prescribers to gastroenterologists, internalists and gastric surgeons. I do this for two reasons. First, treatment course for IBD is almost always determined by specialists (Casellas et al., 2004). Second, almost all payments related to aminosalicylates are given to physicians in those specialties. Additionally, I restrict my sample to physicians for whom I have information on patient population characteristics. I use these characteristics to estimate the share of physician beneficiaries who suffer from IBD. See section 5 for details.

Medicare Part D aminosalicylates prescriptions are described in table 1. There are three major Aminosalicylate molecules[4]. Sulfasalazine was first introduced to the market in 1950. It is considered equivalent to other aminosalicylates in efficacy, yet is less tolerable than Mesalamine and Balsalzide due to its sulfa composition (Nikfar et al., 2009). Mesalamine and Balsalzide are considered equivalent in efficacy and tolerability, though

[4]Olsalazine is a fourth aminosalicylate molecule; I do not include it in my analysis as it was prescribed to a negligible number of Medicare Part D patients in 2013-2015.

Balsalzide has no delayed release formulation.

More than three quarters of Aminosalicylate-treated patients were given Mesalamine, despite the higher costs associated with this molecule. While a generic Mesalamine is available on the market, it is only available as topical formulation, which is considered an inferior delivery system to the oral deliver (by tablet or capsule) of the branded Mesalamine drugs. With the exception of Delzicol (introduced March 2013), the Mesalamine brands are mature products, and have been on the market, at minimum, for more than 5 years by 2013.

2.2 Pharmaceutical Payments Data

A provision of the Affordable Care Act requires that manufacturers of drugs and medical goods ("Applicable Manufacturers") provide a yearly report of all payments and transfers made to active physicians and teaching hospitals. This data is made publicly available on the Open Payments website. The dataset contains information on all transfers valued at $10 or more (whether cash, service or product) made by applicable manufacturers to physicians. Data is released annually, and currently covers 2013Q3 through 2016Q4. The dataset is disaggregated, and contains information on individual payments, including payment value, nature, date and any product (drug or medical good) that is associated with it.

A provision of the act prohibits physicians from being identified by their NPI in the dataset. I match physicians across the Open Payments and Medicare Part D datasets using other identifiers - full names and detailed addresses. In this manner, I am able to match 80% of physicians in the Open Payments data set with physicians in the Part D dataset.

Table 2 provides a summary of payments by nature for the data used in this paper's analysis. The majority of payments are for dining or educational purposes (e.g., textbooks and journals), and tend to be of low monetary value. Other types of payments are less common, but of much higher value. These include travel and lodging expenses, consulting fees, and speaking fees.

In the following analysis I focus on low value, high frequency payments, which are

Table 1: Aminosalicylates Market in 2013-2015

Molecule	Brand	Entry	Producer	Cost per day		Prescribers	Patients	
				Mean	S.D.		Count	% of class
Balsalazide	Generic	2000		3.94	1.74	6,209	13,049	13.13
	Molecule totals:					6,209	13,049	13.13
Mesalamine	Generic	2007		12.31	3.98	513	581	0.58
	Apriso	2008	Salix	11.54	2.29	7,941	16,549	16.65
	Asacol	1992	Warner Chilcott	13.36	3.26	1,184	2,908	2.93
	Asacol HD	2008	Warner Chilcott	18.49	6.50	7,679	13,374	13.46
	Canasa	2001	Aptalis Pharma	23.95	5.51	1,673	3,440	3.46
	Delzicol	2013	Warner Chilcott	14.62	4.85	3,680	5,016	5.05
	Lialda	2007	Shire	18.47	5.13	11,488	26,727	26.89
	Pentasa	1993	Shire	22.48	6.69	5,158	7,809	7.86
	Molecule totals:					39,316	76,404	76.87
Sulfasalazine	Generic	1950		0.89	0.44	4,964	9,212	9.27
	Generic (DR)	1982		1.30	0.50	544	726	0.73
	Molecule totals:					5,508	9,938	10.00

Notes: Aminosalicylates prescribed to Medicare Part-D beneficiaries in 2013-2015. For drugs prescribed by gastroenterologists, internalists, and gastric surgeons. Average costs includes ingredient cost, dispensing fee, and sales tax, and is based on amount paid by all parties (beneficiary, government, and any third-party payer). Number of patients imputed from claims data.

Table 2: Distribution of Payments by Nature

Nature of payment	Number of Physicians	Total Count	Total value (in $1,000s)	Payment (in $) Mean	SD
Food and beverage	8,670	108,409	1,600	16.8	16.2
Education	1,821	3,009	44	15.3	10.1
Speaking fees	183	633	128	365	915
Honoraria	44	162	308	1,739	761
Travel and lodging	39	269	94.2	435	993
Consulting fees	12	16	58.4	2,810	2,432
Total	9,274	112,498	2,232	19.1	69.3

Notes: Payments associated with Aminosalicylates brands given to gastroenterologists, internalists and gastric surgeons who participate in Medicare Part D, in 2013Q3-2015.

associated with the practice of detailing (marketing to physicians). Lunches are described as "the [pharma sales] reps' weapon of choice" (Oldani, 2004). Survey data suggests that detailing is often accompanied by dining, and in much higher frequency than drug samples (Campbell et al., 2007, 2010). My own discussions with a sales director at company X, one of the largest pharmaceutical producers in the US market, confirm this; physicians are becoming less amenable to detailing visits, and providing lunches is quickly becoming the only way of gaining access to physicians' practices.

The small number of physicians who receive higher valued payments results in extremely low estimation power, particularly in the type of analysis I perform in this paper, which relies on within-physician variation to recover causal estimates. However, my identification strategy can be used in other drug classes, where high value payments are more ubiquitous.

3 Methodology

3.1 Illustration

I am interested in estimating the effect of pharmaceutical payments (which proxy for detailing) on physician prescription. Namely, I am interested in a regression of the form

$$y_{itj} = \alpha + \sum_{h=0}^{t} \beta_{t-h} d_{ihj} + \gamma_{ij} + \tau_{tj} + \epsilon_{itj} \tag{1}$$

where y_{ijt} is some physician prescription outcome, and $\{d_{i1j}, d_{i2j}, ..., d_{itj}\}$ is the sequence of payments (related to drug j) the physician has received. γ_{ij} and τ_{tj} capture {physician,drug} and {period,drug} fixed effects, respectively. The sequence $\{d_{i1j}, d_{i2j}, ..., d_{itj}\}$ is refered to as the "goodwill stock" in the marketing literature, and is often assumed to have a constant decay rate.

The specification in equation (1) allows for physician behavior to be influenced by prior payments in a flexible manner. Identifying the causal effects of these payments relays on the mean independence assumption, $E[\epsilon_{itj}|\{d_{ihj}\}_{h=0}^{t}, \gamma_{ij}, \tau_{tj}] = 0$ for all t.

Previous research into the effects of payments and detailing on physician prescription relied on physician fixed effects, γ_{ij}, to maintain the mean independence assumption (i.e., resolve the endogeneity). In section 7.1 of the appendix I show that physician FE are not sufficient for recovering causal effects, as pharmaceutical companies select physicians in and out of payments dynamically. Simply put, regressions of the form in (1) will fail to identify the effects of pharma payments, as pharmaceutical companies respond to temporal ϵ_{itj} shocks.

3.2 Identification

I identify the causal effects of payments and detailing by focusing on drugs that undergo sharp changes to their marketing strategies as a result of company takeover by a competing pharma. For three of the four aminosalicylate brands which underwent acquisition in 2013-2015, these marketing changes are characterized by a dramatic decrease in the

Table 3: Pharma Acquisition and Drug Related Payments

Drug brand:	Asacol HD	Delzicol	Canasa	Apriso
Target pharma	Warner Chilcott	Warner Chilcott	Aptalis Pharma	Salix
Acquiring pharma	Actavis	Actavis	Forest	Valeant
Acquisition date	10/01/2013	10/01/2013	01/08/2014	04/01/2015
Physician counts				
Never received payment	7,251	6,648	7,626	6,783
Received pre-acquisition	1,480	68	822	2,223
Received post-acquisition	254	2,362	529	31
Both pre- and post-acquisition	183	90	191	131
Pr(stop receiving after acquisition)	0.975	0.430	0.811	0.944

Notes: For payments associated with Aminosalicylates brands given to gastroenterologists, internalists and gastric surgeons who participate in Medicare Part D.

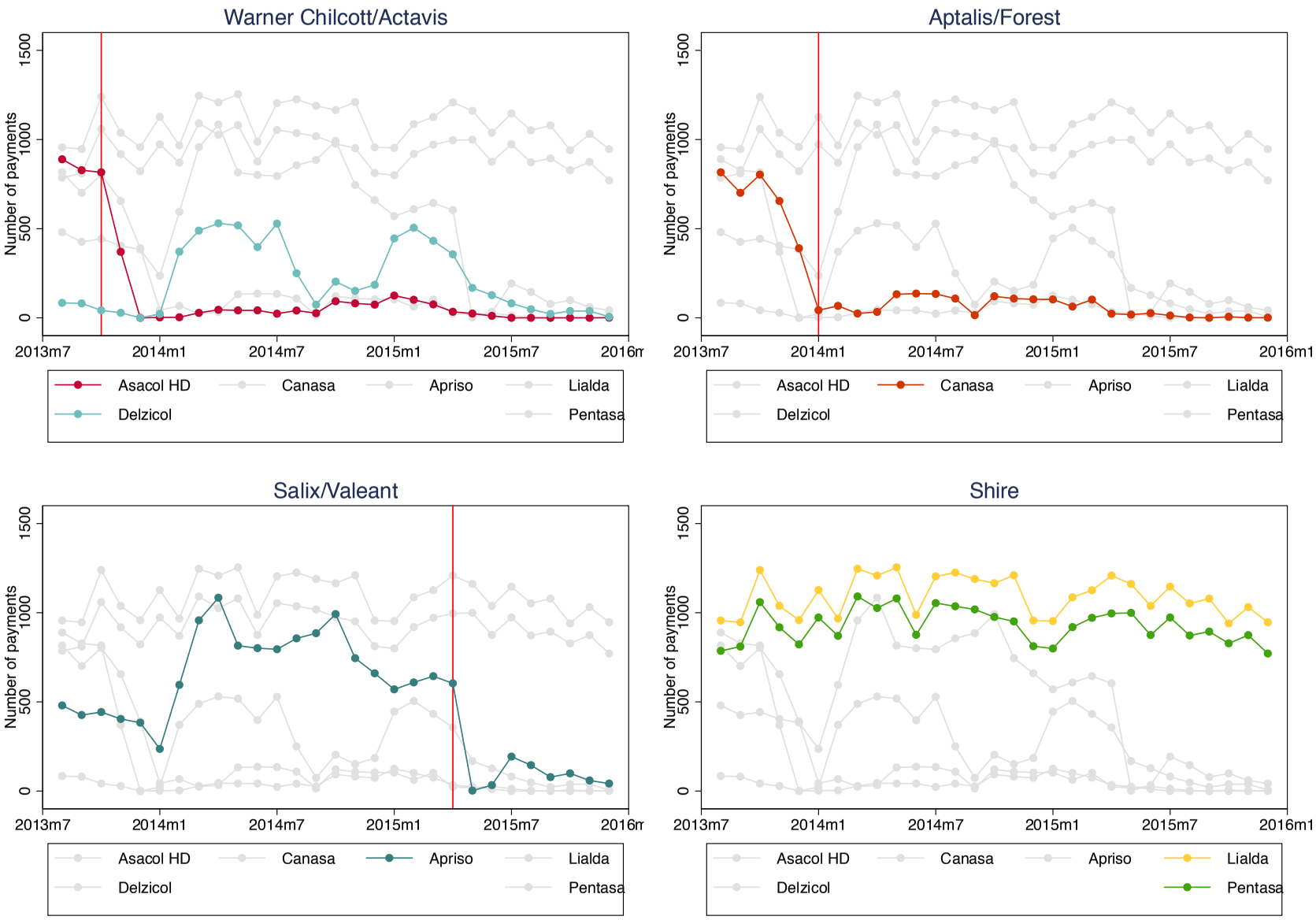
number of physicians who receive drug-related payments, as shown in Table 3.[5] The vast majority (81-97 percent) of physicians who received payments for Asacol HD, Canasa or Apriso prior to the pharma acquisition were unlikely to continue receiving payments from the acquiring drug producer.

Figure 1 shows how monthly payments vary with pharma acquisition. For Asacol HD, Canasa and Apriso payments cease almost completely around the time of acquisition. Delzicol undergoes the opposite process, with few payments prior to acquisition, and an intensive payments schedule in 2014 and 2015, post acquisition. Pentasa and Lialda, which are owned by Shire, exhibit payment patterns that are relatively constant over time.

The identifying assumption in my analysis is that physicians who stopped receiving payments immediately after pharma acquisition have been “dropped" due to the acquisition itself, and not as a response to any physician-drug characteristic or temporal shock. In terms of the regression specified in equation (1), I use variation in $\{d_{ihj}\}_{h=0}^{t}$ that is as-

[5]This is not a universal result: Some pharmaceutical companies do not change payments schedules post-acquisition, or change it in a different manner, like altering the frequency of payments. However, a substantial number of pharmaceutical companies respond by a near complete cessation of payments after acquisitions.

Figure 1: Drug Payments in face of Acquisition



Notes: Total number of payments associated with Aminosalicylates brands given to gastroenterologists, internalists and gastric surgeons who participate in Medicare part D, in 2013Q3-2015. Vertical line is drawn at the month the pharmaceutical acquisition was completed.

sumed to be uncorrelated with ϵ_{itj}. Note that physicians who began receiving payments at acquisition still suffer from selection bias as described in section 7.1, and cannot be used to identify causal effects.

3.3 Estimation

The exogenous variation in payments I exploit is given by $\{d_{i0j} = 1, d_{i1j} = 0, ..., d_{iTj} = 0\}$, where period 0 is to the last period (year) before pharma acquisition, and T is the last period I observe. This sets period 0 as 2013 for Asacol HD and Canasa, and 2014 for Apriso. Using different years as baseline periods for different brands does not bias trend estimates, as these are brand-specific. Thus, $T = 2$ for Asacol HD and Canasa, and $T = 1$ for Apriso. The model in equation (1) can therefore be rewritten as:

$$y_{itj} = \alpha + \beta_{t,j} d_{i0j} + \gamma_{ij} + \tau_{tj} + \epsilon_{itj} \tag{2}$$

for $t = 0, ..., T$, and where $\beta_{t-1,j}$ is allowed to vary by brand (j). As before, γ_{ij} and τ_{tj} capture {physician,drug} and {period,drug} fixed effects, respectively.

The formulation given in equation 2 can be rewritten as a difference-in-difference model, by decomposing the time-varying coefficient $\beta_{t,j}$ to constant and time-varying components: Let

$$\beta_{t,j} = \kappa_j + \theta_{t,j} \cdot \tau_{tj} \tag{3}$$

then, plugging the value for $\beta_{t,j}$ into equation 2,

$$y_{itj} = \alpha + \kappa_j d_{i0j} + \theta_{t,j} d_{i0j} \tau_{tj} + \gamma_{ij} + \tau_{tj} + \epsilon_{itj} \tag{4}$$

where I set $\theta_{t,j} = 0$ for $t = 0$. The coefficient κ_j captures any baseline difference in y_{itj} between paid and unpaid physicians in period 0. This coefficient does not only capture the contemporaneous effect of payment, d_{i0j}, but also any persistent effects from payments given to the physician before period 0, which are correlated with d_{i0j}, as well as selection bias into payments, as physicians with higher values of y_{itj} are likelier to be targeted for detailing and payments. I therefore can only causally estimate $\theta_{t,j}$, the changes to prescriptions as measured by y_{itj}, following payment cessation at period 0.

4 Results

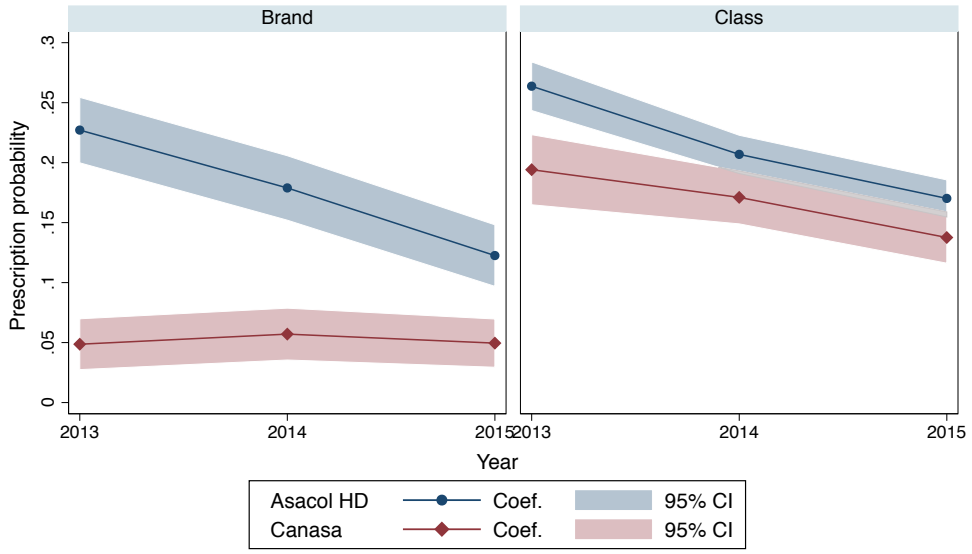
I estimate the Difference-in-Difference model presented in (4) for various measures of physician prescriptions. I perform a within transformation to eliminate γ_{ij}, and include the {period,drug} fixed effects τ_{jt} as dummy variables. Estimation results are presented in table 4. I measure the effects of payments on brand prescriptions using two dependent variables: One, an indicator function receiving value if the physician prescribed the brand (transforming the regression to a LPM). The other, the log of total days of supply prescribed for the brand. I also examine the effect of brand-related payment on overall class prescriptions, by using an indicator function for prescribing any drug from the aminosalicylate class of drugs, and a log of the the total days supply of aminosalicylates prescribed by the physician.

My main finding is that physicians who stopped receiving drug related payments at a given year, were less likely to prescribe aminosalicylate drug therapy of any kind in the following years, with and average decrease of 3.3 (Apriso) to 5.4 (Asacol HD) percentage points one year after payment cessation, and 6.5 (Canasa) to 9.2 (Asacol HD) decrease two years after cessation. This result appears across different brands, owned by different pharmaceutical companies, for payment cessation occurring at different periods (Asacol HD and Canasa in end of 2013 , Apriso in 2015). I also find that physicians who stopped receiving payments related to Asacol HD were less likely to prescribe that brand in the following year, with a decrease of 4.6 percentage points in 2014, and 10.5 percentage points in 2015. Similar patterns appear when examining payment effects on prescription volume, as measured by the log of prescription days.

A potential reason for why Asacol HD shows brand-level effects but Canasa does not, could be differences in baseline prescription probabilities. Figure 2 plots the overall difference in the probability of prescribing brand and class between treatment and control group, $\kappa_j + \theta_{jt}$, for Asacol HD and Canasa, using a specification of model (4) without {physician,drug} fixed effects.[6] Note that the baseline difference between the groups, κ_j, is not a causal estimate of payment on prescription in 2013, as it additionally captures any

[6] I still identify causal effects of payments without these fixed effects. See Lechner et al. (2015).

Figure 2: Probability of prescribing brand and class following payment cessation



Notes: Plotting $\beta_{t,j} = \kappa_j + \theta_{t,j}$ estimates of the model described in equation 4, excluding {physician,drug} fixed effects.

selection bias into payments, and any remaining effects from payments given in earlier period (since these are correlated with payments at year t). Physicians who received payments related to Asacol HD were far likelier to prescribe the brand in 2013 (20 percentage points more), while those who received payments for Canasa were just 3 percentage points likelier to prescribe the brand.

As figure 2 demonstrates, the decrease in prescribing probabilities suggests that these previously paid physicians are reverting back to prescribing behavior that is more similar to that of an unpaid physician. As physicians receiving payments for Canasa were not much likelier to prescribe the brand than the unpaid-physician, they do not "revert back" to prescribing less of the brand after cessation. The short span of my panel data prevents me from seeing what proportion of the difference between previously-paid and unpaid physicians will vanish, given sufficient time.

Table 4: Difference-in-Difference estimates of stopping payments effects

		Dependent Variable			
		Brand Level		Class Level	
Brand	Period	1(prescribe)	log(days supply+1)	1(prescribe)	log(days supply+1)
Apriso	$+1$	0.025	0.193^{*}	-0.047^{**}	-0.225^{**}
		(0.014)	(0.088)	(0.012)	(0.078)
Asacol HD	$+1$	-0.046^{**}	-0.280^{**}	-0.054^{**}	-0.219^{**}
		(0.013)	(0.086)	(0.012)	(0.075)
	$+2$	-0.105^{**}	-0.680^{**}	-0.092^{**}	-0.429^{**}
		(0.015)	(0.097)	(0.012)	(0.080)
Canasa	$+1$	0.008	0.050	-0.033^{*}	-0.119
		(0.012)	(0.071)	(0.016)	(0.105)
	$+2$	0.001	0.002	-0.065^{**}	-0.316^{**}
		(0.012)	(0.076)	(0.018)	(0.120)
Adj. R-squared		0.01	0.01	0.03	0.04
Observations		$107,076$	$107,076$	$107,076$	$107,076$

Notes: Difference-in-Difference estimations of the model described in equation 4, with different dependent variables. The first and third dependent variables are indicator functions for prescribing the brand, and for prescribing any drug from the pharmacologic class, respectively. The second and fourth dependent variables are logs of the number of total prescription days (plus one) given for the drug brand, and for the pharmacologic class, respectively. Adjusted R-squared refers to within {physician,drug} variation. physician-drug clustered errors in parentheses. * Significant at the 5% level, ** Significant at the 1% level.

4.1 Decomposing Treatment Effects

Much of the research into detailing effects has focused on the two hypothesized roles of detailing; persuasive and informative. Some evidence of the aggregate effects of detailing led it to be interpreted as persuasive: Continued marketing of mature products (Leffler, 1981), slowing down generic incursion into branded drug markets (Hurwitz and Caves, 1988), and evidence of lowered physicians' price sensitivity (Rizzo, 1999). This discussion extends to the general marketing literature. Studying yogurt advertisements, Ackerberg (2001) argues that the informative and persuasive roles of marketing can be identified by variation across inexperienced and experienced consumers.

More recent literature has attempted to empirically decompose the two effects: Narayanan and Manchanda (2009) identify the informative and persuasive roles of detailing by function form assumptions, where the informative component of detailing affecting physician's belief about the efficacy of the drug, and the persuasive component entering physician's utility as a goodwill stock. They conclude that the persuasive effect accounts for 35-41 percent of detailing effect for two erectile dysfunction brands. Ching and Ishihara (2010) use comarketing agreements, where two (or more) pharmaceutical producers market the same molecule under different brand names, to identify the different roles of detailing. Their identifying assumption is that brand-specific effects are of a persuasive role, while molecule-specific effects are of an informative role. They find that informative effect is mainly responsible for molecule level demand, while the persuasive effect dominates brand level demand.

I suggest a different decomposition from the informative/persuasive division, but one that I argue is closely related to it. I decompose payment treatment effects into persistent and transitory components. The permanent component is defined by $\beta_{T,j} = \kappa_j + \theta_{T,j}$, the remaining cross-sectional difference in outcome between paid and unpaid physicians, T years after payment cessation. The transitory component is therefore given by:

$$\kappa_j - \beta_{T,j} = \kappa_j - (\kappa_j + \theta_{T,j}) = -\theta_{T,j}$$

These persistent effects are not identified as causal. As κ_j has no causal interpretation. As κ_j is likely bias upwards from any causal contemporaneous effect of payment on prescrib-

ing, my estimate of the permanent component can be considered an upper bound on the size of the causal permanent component.

I find that at most 54.9% (S.E. 5.4%) of Asacol HD brand effect is permanent, and 64.5% (S.E. 3.6%) of Asacol HD class effect is permanent. For payments related to Canasa and Apriso, I find that at most 70.8% (S.E. 7.4%) and 81.7% (S.E. 6.5%) of class effect are permanent, respectively.

I interpret these results by relating them to the common information/persuasion decomposition. If one assumes that information has a permanent effect on physician prescribing, while persuasion has a decaying effect (a common assumption in the marketing literature), then one could interpret the permanent component as an upper bound of the informative effects of detailing, as proxied by payments. Under this interpretation, my results conform with previous work by Ching and Ishihara (2010), who found that chemical-level (class level) effects are more informative in role then brand level effects.

4.2 Treatment Effect Heterogeneity

I estimate treatment effect heterogeneity by modelling the coefficients of interest as flexible functions of physician practice characteristics. Namely, I allow treatment effects to vary as a function of different physician practice characteristics which I model by cubic B-splines. Estimates of the effects of payment cessation on the probability of prescribing from the class two years after payment cessation, for different underlying variables, are presented in figure 3. Due to short length of my panel, I include results for just one year later for Apriso.

Analysis suggests that physicians with larger practices, as measured by the number of patients in a given year, are more affected by payment cessation. This result is consistent across the three brands. Other estimates suggest divergent patterns across brands. For example, physicians with older patients are more affected by Asacol HD payment cessation, but not Apriso or Canasa payment cessations. Physicians whose practice is located in more impoverished locales (as measured by the per capita income in the 5 digit zipcode) are more affected by Asacol HD payment cessation, while Canasa payment cessation seem to

affect physicians is more affluent locales.

4.3 Sensitivity Analysis

4.3.1 Payment Intensity

I perform an analysis similar to the one given in equation (4), but include a linear term for the *number* of payments the physician has received before treatment cessation. Let p_{itj} be the number of payments physician i received for drug j in period t, then $d_{itj} = 1(p_{itj} > 0)$. I estimate

$$y_{itj} = \alpha + \kappa_j d_{i0j} + \lambda_j p_{i0t} + \theta_{t,j} d_{i0j} \tau_{tj} + \pi_{t,j} p_{i0j} \tau_{tj} + \gamma_{ij} + \tau_{tj} + \epsilon_{itj} \tag{5}$$

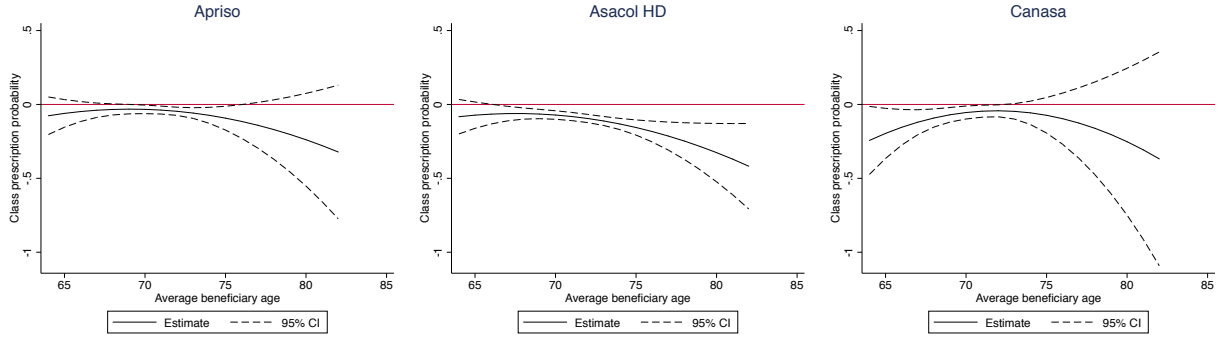
where λ_j captures baseline differences between paid physicians as a linear function of the number of payments they received for brand j, $\theta_{\cdot,j}$ capture the constant effect of receiving payments on changes to prescribing, and $\pi_{\cdot,j}$ capture the effect of receiving one additional payment prior to complete payment cessation.

Results are presented in table 5. For Asacol HD, I find that additional payments lessen the reduction in brand prescription post payment cessation, but not the reduction in total class prescriptions. For Apriso, I find that additional payments marginally lessen the reduction in class prescription post-cessation, though the difference is not statistically significant. Results for Canasa exhibit a different pattern. Physicians who received just a single payment related to Canasa prior to cessation were 1.2 percentage points less likely to prescribe drug therapy post-cessation, but each additional payment pre-cessation reduces post-cessation probability of prescribing drug therapy by an additional 3 percentage points.

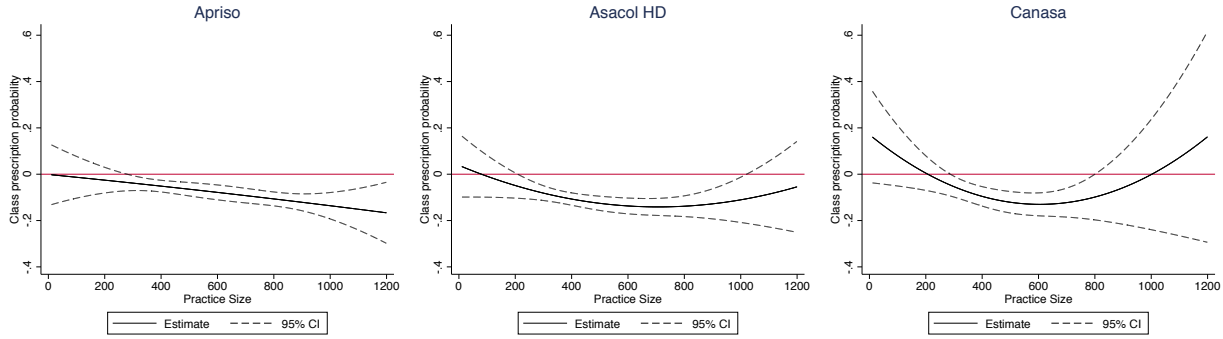
4.3.2 Placebo Tests

My estimates for changes to physician class-level prescription post payment cessation are similar across the three aminosalicylate drugs that undergo acquisition (this excluding Delzicol, for which few physicians received payments pre-acquisition), this despite the fact the Asacol HD, Apriso and Canasa are owned by different pharma, marketed to different

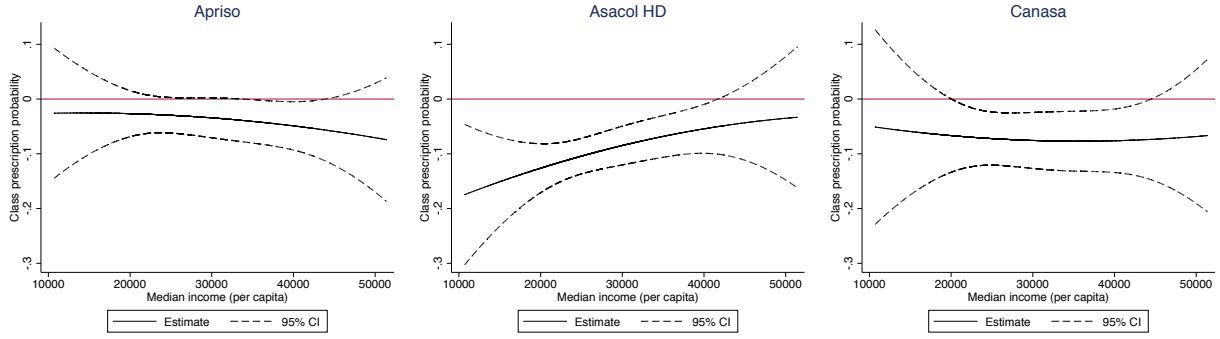
Figure 3: Effect Heterogeneity: Probability of prescribing from the class



(a) Average age of physician's beneficiaries



(b) Size of physician's practice



(c) Median per capita income

Notes: Effects of stopping payments on the probability the physician would prescribe any aminosalicylate therapy, as a flexible function (cubic B-splines) of various physician characteristics.

Table 5: Sensitivity Analysis: Treatment Intensity

			Dependent Variable			
			Brand Level		Class Level	
Brand	Period	Effect	1(prescribe)	log(days supply+1)	1(prescribe)	log(days supply+1)
Apriso	$t+1$	Constant	-0.011	-0.026	-0.059**	-0.327**
			(0.022)	(0.141)	(0.017)	(0.112)
		Linear	0.008	0.049	0.002	0.019
			(0.004)	(0.027)	(0.002)	(0.015)
Asacol HD	$t+1$	Constant	-0.097**	-0.604**	-0.043*	-0.112
			(0.028)	(0.177)	(0.021)	(0.138)
		Linear	0.029*	0.181*	-0.007	-0.064
			(0.014)	(0.091)	(0.011)	(0.073)
	$t+2$	Constant	-0.126**	-0.817**	-0.089**	-0.376*
			(0.031)	(0.198)	(0.022)	(0.146)
		Linear	0.012	0.074	-0.002	-0.034
			(0.017)	(0.108)	(0.011)	(0.074)
Canasa	$t+1$	Constant	-0.003	-0.043	0.020	0.174
			(0.027)	(0.160)	(0.031)	(0.204)
		Linear	0.004	0.036	-0.019*	-0.107
			(0.009)	(0.052)	(0.009)	(0.058)
	$t+2$	Constant	0.012	0.064	0.017	0.196
			(0.025)	(0.147)	(0.036)	(0.242)
		Linear	-0.003	-0.012	-0.029**	-0.180**
			(0.007)	(0.040)	(0.010)	(0.068)
Adj. R-squared			0.01	0.01	0.03	0.04
Observations			103,914	103,914	103,914	103,914

Notes: Difference-in-Difference estimations of the model described in equation 5, with different dependent variables. The first and third dependent variables are indicator functions for prescribing the brand, and for prescribing any drug from the pharmacologic class, respectively. The second and fourth dependent variables are logs of the number of total prescription days (plus one) given for the drug brand, and for the pharmacologic class, respectively. Adjusted R-squared refers to within {physician,drug} variation. physician-drug clustered errors in parentheses. * Significant at the 5% level, ** Significant at the 1% level.

physicians, and have undergone payment cessation in different periods. This similarity might leave one concerned that my results are not driven by my identification strategy (and are therefore not, in fact, causal) or, even worse, are an artifact of my estimation method.

To address such concerns, I perform the following placebo test. I apply my identification strategy and estimation to the two aminosalicylate brands that did not undergo acquisition, Lialda and Pentasa, treating them as though they were acquired the same time as Canasa, and estimating the effects of payment cessation on paid physicians.[7] These payment cessations are endogenous, a result of the pharmaceutical company (Shire) selecting these physicians out of payments, as opposed to the payment cessations which I claim to be exogenous, as a result of actual acquisition.

I also subject Apriso to the same placebo treatment, using the Canasa acquisition date in 2014, rather than the actual 2015 Apriso acquisition date. By using Apriso, a drug that underwent acquisition in 2015, I hope to alleviate concerns that Asacol HD, Canasa and Apriso are somehow different from the drugs that do not undergo acquisition, Lialda and Pentasa, in ways that may affect physician behavior post payment cessation.

Placebo Results are presented in table 6. Results are markedly different from those given in table 4, for drugs that underwent ostensibly-exogenous payment cessation. I find significant positive effects on brand prescribing for Apriso and Lialda, and a decrease in the probability of prescribing Pentasa two years after cessation. More importantly, I find no class-level effects on the probability of prescription or on the amount supplied, for any of the three drugs.

4.4 Alternative Drug Therapies

Aminosalicylates are the mainstay drug class for treating IBD (Burger and Travis, 2011).[8] However, other drug classes may be used for either inducing or maintaining disease remission. Are physicians simply substituting aminosalicylate drug therapy to drug therapy

[7] Results are robust to the specific point in time I assign to this placebo "acquisition."

[8] This is particularly true for mild-to-moderate ulcerative colitis. Aminosalicylates are less effective in treating Crohn's disease or severe ulcerative colitis

Table 6: Placebo Test: Brands that Do Not Undergo Ownership Change

		Dependent Variable			
		Brand Level		Class Level	
Brand	Period	1(prescribe)	log(days supply+1)	1(prescribe)	log(days supply+1)
Apriso	$t+1$	0.015	0.103	-0.034	-0.113
		(0.029)	(0.181)	(0.026)	(0.168)
	$t+2$	0.082*	0.546**	-0.014	0.079
		(0.032)	(0.203)	(0.027)	(0.180)
Lialda	$t+1$	0.033	0.298	-0.011	0.079
		(0.037)	(0.233)	(0.032)	(0.210)
	$t+2$	0.078	0.615*	-0.031	-0.027
		(0.043)	(0.275)	(0.036)	(0.240)
Pentasa	$t+1$	-0.005	-0.006	-0.018	0.053
		(0.025)	(0.156)	(0.032)	(0.208)
	$t+2$	-0.057*	-0.340	-0.039	-0.049
		(0.027)	(0.176)	(0.034)	(0.229)
Adj. R-squared		0.02	0.02	0.03	0.04
Observations		88,720	88,720	88,720	88,720

Notes: Difference-in-Difference estimations of the model described in equation 4, with different dependent variables. The first and third dependent variables are indicator functions for prescribing the brand, and for prescribing any drug from the pharmacologic class, respectively. The second and fourth dependent variables are logs of the number of total prescription days (plus one) given for the drug brand, and for the pharmacologic class, respectively. Adjusted R-squared refers to within {physician,drug} variation. physician-drug clustered errors in parentheses. * Significant at the 5% level, ** Significant at the 1% level.

using a different pharmacologic class? In this section, I show that there is little evidence that payment cessations for aminosalicylate brands have any effect on prescribing other drug classes used to treat IBD.

There are three other drug classes, apart from aminosalicylates, that can be used to treat IBD. Steroids (particularly budesonide and hydrocortisone) are effective in inducing remission, but associated with significant complications, and are therefore not used for remission maintenance (Feuerstein and Cheifetz, 2014). Azathioprine (AZA) can be used both in induction and maintenance, yet is a known human carinogen (Pasternak et al., 2013; Pedersen et al., 2010). Finally, anti-TNF agents are effective both in induction and maintenance, but are significantly costlier than aminosalicylates. Both AZA and anti-TNF agents have a slow onset of action, and are typically combined with steroids in inducing disease remission.

I estimate the effects of payments related to aminosalicylate class brands (Asacol HD, Canasa and Apriso) on prescribing from other drug classes. I estimate a model closely related to equation 4. For each drug class c in the the set of drug classes (apart from aminosalicylates) that can be used to treat IBD $\mathscr{C}$ (steroids, AZA, anti-TNF), and for each aminosalicylate brand $j \in J$ (Asacol HD, Apriso, Canasa), I estimate

$$y_{itc} = \alpha_c + \sum_{jinJ} (\kappa_{cj} d_{i0j} + \theta_{t,c,j} d_{i0j} \tau_{tj} + \gamma_{icj} + \tau_{tcj}) + \sum_{k \in \mathscr{C}} \sum_{h=0}^{t} \beta_{t-h,k,c} D_{ihk} + \epsilon_{itc} \tag{6}$$

where y_{itc} is a drug class-level variable for physician i in period t, d_{i0j} is an indicator for receiving payment related to aminosalicylate brand j at period 0, and D_{ihk} is an indicator for receiving payment related to *any* brand in drug class $k \in \mathscr{C}$ at period h. γ_{icj} and τ_{tcj} capture {physician,drug class, aminosalicylate brand} and {period,drug class, aminosalicylate brand} fixed effects, respectively.

As before, I consider two types of outcome variables. The first is an indicator variable receiving value if the physician prescribed from the class. The second is the natural log of the number of prescription days prescribed by the physician. I control for payments related to any other brands in these classes.[9]

[9] In practice, this means controlling for payments for related to the anti-TNF agents Cimizia, Humira and Simponi.

Results are presented in table 7. With the exception of an increase in steroid prescriptions for physicians who stopped receiving payments related to Asacol HD, I find that payment cessation of aminosalicylate brands does not affect prescribing of drug classes other than aminosalicylates. In other words, I find that physicians who stop receiving payments related to aminosalicylates prescribe less from that pharmacologic class, but do not shift to other drug therapies for IBD.

5 A Model of Physician Prescription

I estimate a simple discrete choice model of physician prescription. I employ and estimate a model for several reasons: First, to fit my results in the framework that is common in the literature, which is set at the physician-patient level. Second, to allow a clear interpretation of my results in terms of physician decision making; namely, the decision to prescribe a specific brand over another, or more importantly, to prescribe from the entire class over an outside option. Finally, the model allows me to produce counterfactuals that take both the extensive margin (probability of prescribing) and intensive margin (duration of prescribing) into account, an flexibly predict the brand substitution pattern that arises after payments cease. However, as I do not observe patient level data, I employ an aggregate logit model which uses physician-level drug shares to infer on patient-month level decisions, similar to the methodology developed by Berry et al. (1995).

In period t, physician i has a set of patients N_{it} with a specific medical condition (ulcerative colitis or Crohn's disease). I assume that N_{it} is fully identified by the physician, meaning that no patient is misdiagnosed. Each period, the physician selects a drug therapy $j \in J_t$ for each patient $n \in N_{ict}$ to maximize U_{intj},

$$U_{intj} = \sum_{h=0}^{t} \delta_{t-h} d_{ihj} + \eta_{intj} \tag{7}$$

Where $\{d_{i1j}, d_{i2j}, ..., d_{itj}\}$ is the sequence of drug detailing the physician has received.

The unobservables are denoted by η_{intj}. I decompose η_{intj} into separate unobservable components:

$$\eta_{intj} = \eta_{ij} + \eta_{tj} + \eta_{int} + \nu_{itj} + \epsilon_{intj} \tag{8}$$

Table 7: Stopping Aminosalicylates Payments: Effects on Other Drug Classes

		Cortisteriods		Azathioprine		Anti-TNF	
Brand	Period	1(prescribe)	log(days supply)	1(prescribe)	log(days supply)	1(prescribe)	log(days supply)
Apriso	+1	0.021	0.134	0.006	0.043	0.000	-0.001
		(0.015)	(0.094)	(0.013)	(0.086)	(0.013)	(0.079)
Asacol HD	+1	0.007	0.052	0.009	0.065	0.007	0.028
		(0.014)	(0.085)	(0.011)	(0.072)	(0.011)	(0.067)
Asacol HD	+2	0.029	0.204*	0.015	0.112	0.022	0.133
		(0.016)	(0.098)	(0.013)	(0.086)	(0.013)	(0.081)
Canasa	+1	0.016	0.086	-0.006	-0.045	-0.005	-0.039
		(0.018)	(0.108)	(0.014)	(0.088)	(0.015)	(0.088)
Canasa	+2	0.039	0.229	-0.014	-0.085	-0.009	-0.065
		(0.020)	(0.125)	(0.016)	(0.104)	(0.018)	(0.107)
Adj. R-squared		0.01	0.01	0.00	0.00	0.03	0.04
Observations		107,076	107,076	107,076	107,076	107,076	107,076

Notes: Difference-in-Difference estimations of the model described in equation 6, with different dependent variables. The first, third and fifth dependent variables are indicator functions for prescribing any drug from the specific pharmacologic class. The second, fourth and sixth dependent variables are logs of the number of total prescription days (plus one) given for the specific pharmacologic class. Adjusted R-squared refers to within {physician,drug} variation. physician-drug clustered errors in parentheses. * Significant at the 5% level, ** Significant at the 1% level.

The first component, η_{ij}, captures any innate predilection physician i might have towards drug j. This includes any atemporal characteristics of physician tastes, clinical knowledge, and practice. The second component, η_{tj}, captures constant and time-varying national preference towards drug j. This component captures any universally known differences in brand efficacies, as well as the effect of any new clinical information (that all physicians are exposed to) about each brand. The third component, η_{int}, captures any time-varying shocks to physician and patient which are not drug-specific. The fourth component, ν_{itj}, captures any time-varying shocks at the {physician,drug} level. Any remaining time-varying {physician,patient,drug}-specific unobservables are captured by the last component, ϵ_{intj}, which is assumed to follow $i.i.d.$ Type I extreme-value distribution.

The physician can also choose not to prescribe any medication $j \in J_{ct}$ to the patient. The utility of not prescribing a drug is given by

$$U_{int0} = \eta_{i0} + \eta_{t0} + \eta_{int} + \nu_{it0} + \epsilon_{int0} \tag{9}$$

I normalize η_{i0}, η_{t0}, and ν_{it0} to zero, as they are not separably identifiable. As the time-varying shocks η_{int} will vanish in estimation, this normalization sets the mean utility of the outside option to zero.

Under the distributional assumptions on ϵ_{intj}, the share of diagnosed patients of physician i in period t who are treated with drug j is given by

$$s_{itj} = \frac{\exp\left(\sum_{h=0}^{t} \delta_{t-h} d_{ihj} + \eta_{ij} + \eta_{tj} + \eta_{int} + \nu_{itj}\right)}{1 + \sum_{k=1}^{J_{ct}} \exp\left(\sum_{h=0}^{t} \delta_{t-h} d_{ihk} + \eta_{ik} + \eta_{tk} + \eta_{int} + \nu_{itk}\right)} \tag{10}$$

5.1 Estimation

Using the share equation described in (10), estimation can be carried out by

$$\log\left(s_{itj}\right) - \log\left(s_{it0}\right) = \sum_{h=0}^{t} \delta_{t-h} d_{ihj} + \eta_{ij} + \eta_{tj} + \nu_{itj} \tag{11}$$

where η_{int} unobservables cancel out by the difference, as they are common to any j choice.

I will not identify the causal effects of payments $\{d_{ihj}\}_{h=0}^{t}$ on prescribing if these are correlated with ϵ_{intj} and ν_{itj}. This would mean that temporal drug-physician variations are correlated with payments, even when controlling for physician-drug, drug-period, and

physician-patient-period fixed effects. As mentioned before, in section 7.1 in the appendix I show that pharmaceutical companies indeed respond to these temporal variations, implying that a straightforward estimation of the model in would not yield causal estimates of λ and $\{\delta_h\}_{h=0}^{t}$. As in my Difference-in-Difference estimation in section 3, I will only use variation in $\{d_{ihj}\}_{h=0}^{t}$ that I assume is exogenous.

Finally, I assume that ν_{itj} are $i.i.d$ errors. I do not consider this to be a strong assumption, for two reasons: First, any physician-specific temporal shocks that are correlated across all drugs $j \in J$ are captured by η_{int}. Second, any serially correlated shocks in the physician's tendency to prescribe drug j is captured by η_{ij}.

The specification I estimate, in equation (12), allows for class-level effects of payments, as captured by γ_{t-h}. This coefficient captures the effect of payment related to drug j on the probability of prescribing any aminosalicylate drug therapy for Colitis or Crohn's. I will allow trends in brand popularity, η_{tj} to vary across physician specialties.

$$\log(s_{itj}) - \log(s_{it0}) = \sum_{k \in J} \sum_{h=0}^{t} (\delta_{t-h,k} \cdot 1(j=k) + \gamma_{t-h,k}) d_{ihk} + \eta_{ij} + \eta_{tj} + \nu_{itj} \tag{12}$$

One might also be interested in a more flexible model, allowing payments to affect each brand separately, rather than restricting effects to brand- and class-level effects. See section 7.2.2 in the appendix for an estimation and discussion of such model.

Estimation of the model in (11) requires knowledge of s_{itj} for each $j \in J$, the share of each drug j in the physician's practice that year, including the share of the outside option, s_{it0}. Nevo (2000) discusses the importance in correctly defining the share of the outside option. I define the total "market" size, for each physician, as the number of her patients who potentially suffer from IBD. The share of the outside option is then the number of physician patients who suffer from IBD minus the number of physician patients treated with IBD. See section 7.2.1 in the appendix for a complete discussion of share estimation.

5.2 Results

Estimates coefficients of the model in equation (12) are presented in table 8. Results suggest that even when controlling for physician innate predilection towards each drug,

and accounting for temporal {physician,patient} shocks, ceasing to receive payments leads to a reduction in the probability of prescribing any aminosalicylate drug therapy to treat IBD patients.

This reduction has two channels. For payments related to Asacol HD, it is a result of a strong decrease in the physician tendency to prescribe the brand itself; the probability of prescribing Asacol HD (over the outside option) is reduced by 21 percent two years after payment cessation. Physician tendency to prescribe other brands is unaffected by the payment cessation, leading to an overall reduction in the probability of prescribing aminosalicylate drug therapy. For payments related to Canasa and Apriso, the decrease is a result of lower physician tendency to prescribe *any* aminosalicylate treatment, regardless of brand; this decrease is measured at 3 percent one year after payment cessation, and 6 percent two years after cessation.

5.3 Counterfactual Analysis

Counterfactual analysis of the model in equation (12) requires estimating a function in which η_{ij} enters nonlinearly. As I cannot identify this variable, I estimate a more restrictive model than that described in (12), where instead of η_{ij} I employ η_i. This fixed effect captures the innate predilection of the physician towards prescribing *any* aminosalicylate drug therapy (over no therapy). As I have multiple observations per-physician per-period, I can identify and estimate this variable. I use these estimates to estimate a counterfactual in which the effect of payments for Asacol HD, Canasa and Apriso does not decay. Alternatively, one could think of this as the counterfactual in which physicians continue to receive drug-related payments for these three brands.

The counterfactual exercise suggests that, if payment effects would not decay, a total of 2140 additional months of drug therapy would have been prescribed in 2015. This represents an increase of 2 percent of the total number of month prescriptions given by previously-paid physicians, or 0.6 percent increase in the total number of months prescribed nationally in 2015. I estimate the total costs of these extra months at $943,000.

The distribution of the difference in drug therapy prescriptions per physician is given

Table 8: Full Model Coefficients and Odds Ratios: Payment Effects

		Coefficients		Odds Ratios	
Brand	Period	Own-effect	Class-effect	Own-effect	Class-effect
Apriso	+1	0.033	−0.028*	1.03	0.97
		(0.050)	(0.013)	(0.05)	(0.01)
Asacol HD	+1	−0.092	0.011	0.91	1.01
		(0.053)	(0.013)	(0.05)	(0.01)
	+2	−0.238**	0.013	0.79	1.01
		(0.057)	(0.014)	(0.04)	(0.01)
Canasa	+1	0.025	−0.027	1.03	0.97
		(0.043)	(0.016)	(0.04)	(0.02)
	+2	0.028	−0.065**	1.03	0.94
		(0.046)	(0.018)	(0.05)	(0.02)

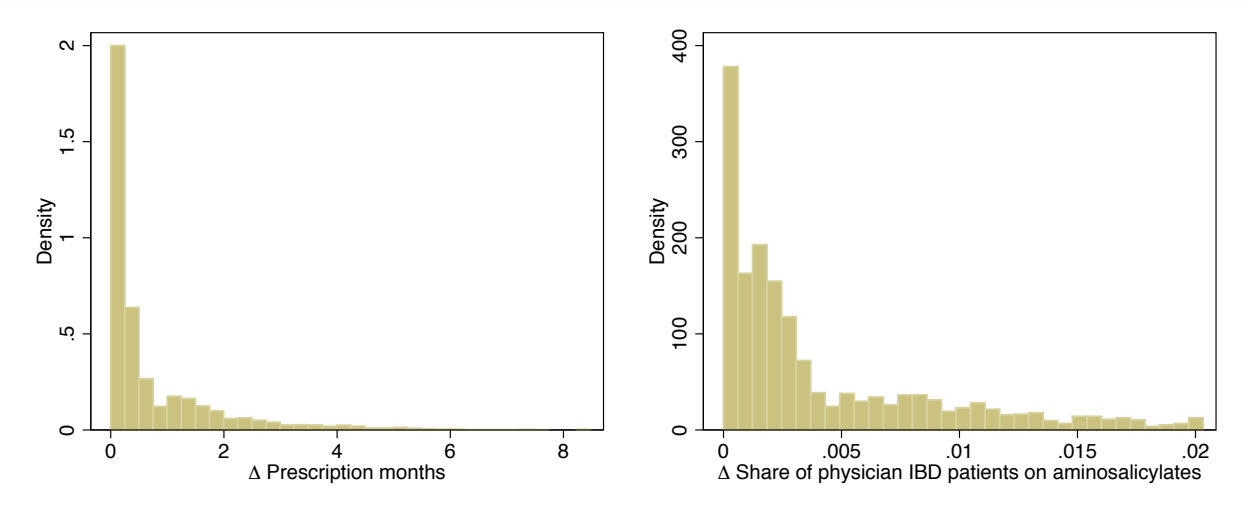
Notes: Estimation of the model detailed in equation 12. Using 387,288 observations. Robust standard errors in parentheses. * Significant at the 5% level, ** Significant at the 1% level.

in figure 4. Nearly half (45.4 percent) of physicians would not have prescribed differently if effects would not decay. For physicians whose behavior changed in the counterfactual, the median increase in aminosalicylate prescriptions is measured in 0.76 months. Over 10 percent would prescribe over 3 additional months.

6 Conclusions

My results can be summarized by two points: First, drug-related payments (which are associated with detailing) increase the likelihood that the physician would prescribe from the class of drugs. Second, the "class expanding" effects of payments decay, leading to a "class shrinking" effect for physicians who stop receiving payments. With the exception of Delzicol, all the aminosalicylate brands are mature products (have been on the market at least six years by the start date of my panel). This would suggest that the prescribing physicians are likely to have experience with these brands. By using the identifying assumptions of Leffler (1981), Ackerberg (2001) and Narayanan and Manchanda (2009), we would as-

Figure 4: Counterfactual: Distribution of additional patient-month prescriptions



Notes: Distribution of increase in prescriptions months in 2015 (Left) and distribution of increase in share of physician's IBD patients who receive aminosalicylate treatment in 2015 (Right). Following the counterfactual scenario described in section 5.3: Continued brand-related payments for 3,115 prescribers.

sume that these payments are unable to provide clinical information to prescribers, and that they therefore only play a persuasive role when affecting prescribing.

I decompose the effect of payments on prescriptions to permanent and transient components. Using baseline differences in brand and class prescription between paid and unpaid physicians, I derive an upper bound for the size of the permanent effect of payments. I find that at most 54.9% (S.E. 5.4%) of Asacol HD brand effect is permanent, and 64.5% (S.E. 3.6%) of Asacol HD class effect is permanent. For payments related to Canasa and Apriso, I find that at most 70.8% (S.E. 7.4%) and 81.7% (S.E. 6.5%) of class effect are permanent, respectively.

If one assumes that information acquired from detailing associated with payments does not decay over time, the permanent component can be interpreted as an upper bound of the informative role of detailing. This interpretation suggests that brand effects are more a result of persuasive detailing than class effects, similarly to the findings of Ching and Ishihara (2010). However, my results also show that drug class effects are also partially persuasive in nature, and that the class-expanding persuasive effect of payments reverses

when payments cease. If my identifying assumption is correct, this would imply that physicians can be persuaded to prescribe drug treatment to patients for whom they would otherwise prescribe none.

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7 Appendix

7.1 Dynamic Selection into Payments

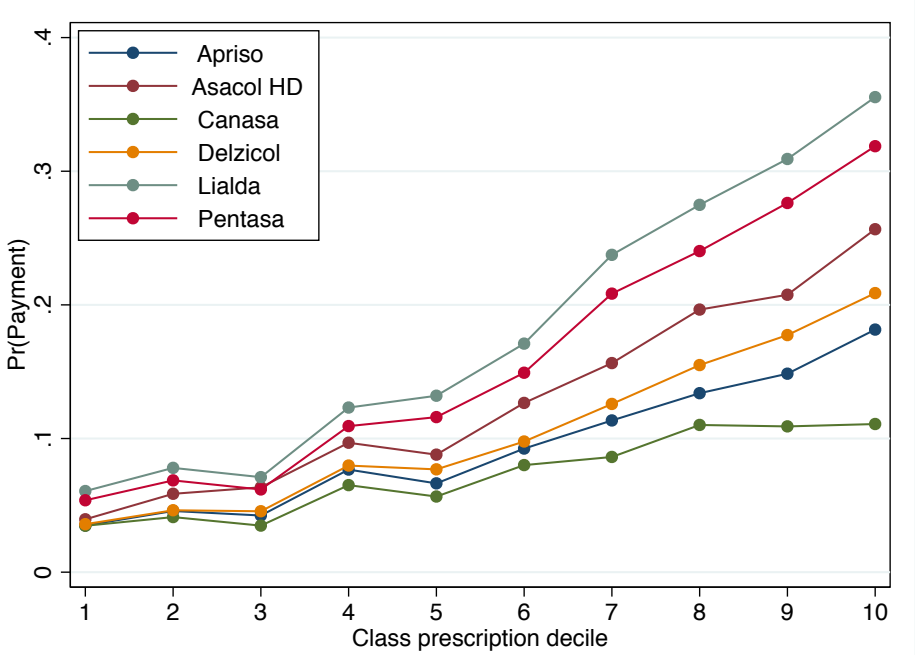
Pharmaceutical companies assign physicians in and out of detailing schedule based on time-varying characteristics of physicians, which are not absorbed by atemporal physician fixed effects. These empirical results are supports by anecdotal evidence: In one leading pharmaceutical company, detailing targets were determined yearly, adjusted quarterly, and varied monthly based on other factors (Manchanda et al., 2004). My own interviews with a pharmaceutical sales manager from a top five pharmaceutical company suggests detailing assignment is adjusted based on a rolling four-week analysis of the physician's prescribing trends.

I plot the probability of a physician receiving treatment based on his decile of class prescription in figure 5. Similar to the finding of Manchanda et al. (2004), I find that physicians in higher prescription deciles are likelier to receive detailing-related payments. This result is true for all detailed brands. However, deciles explain little of the variation in payment assignments.

I perform a linear probability model analysis to test for selection into payments. Results are presented in Table 9. In all models, the dependent variable is an indicator variable receiving value if the physician received a brand-related payment. I divide the regressors into three groups: Variables related to prescribing habits, those related to the physician practice, and those related to the physician herself. Model 1 includes {brand,period} fixed effects, as well as controls for physician specialty and class prescription decile, but no physician fixed effects. Physicians who prescribe more of a brand are likelier to receive payments related to it, as are physicians with larger practices, and those who serve wealthier patients (as measured by the ratio of patients with dual Medicare-Medicaid insurance). Finally, male physicians are likelier to receive payments, as well as less experienced physicians, and those affiliated with hospitals.

Models 2 and 3 include {brand,physician} fixed effects. Model 2 shows that assignment to payments varies with other determinants of physician prescriptions, including shocks to practice size and to physician composition. Model 3 specifically focuses on physicians

Figure 5: Probability of Payment as a Function of Class Prescriptions



who were paid the previous period, to demonstrate that selection *out* of payments is as dynamic as selection *in* to payments.[10] Physicians who suffered a decrease in practice size were likelier to be dropped out of payments, as well as those who have increased proportion of patients with Medicaid coverage. Payment cessation is also associated with physician prescribing behavior: physicians who prescribed more mesalamine (the active components of all paid-brands) were likelier to stop receiving payments, while those who prescribed more of other aminosalicylates were likelier to continue receiving payments.

7.2 Physician Model Addenda

7.2.1 Estimating Shares

I define the total "market" size, for each physician, as the number of the physician's patients who potentially suffer from IBD in the specific year. The share of the outside option is then the number of the physician's patients who suffer from IBD minus the number of

[10] I focus here only on what I term "endogenous" selection out of payments. I do not include payment cessation that resulted from pharmaceutical acquisitions.

Table 9: Determinants of Receiving Pharmaceutical Payments

Variable cat.	Regressor	(1)	(2)	(3)
Prescriptions	Brand cost	0.00386^{**}	0.000278	0.00128
		(0.000341)	(0.000450)	(0.00225)
	Months of class pres.	-0.000323^{**}	0.000293^{**}	0.00165^{**}
		$(3.77e{-}05)$	$(8.48e{-}05)$	(0.000606)
	Months of molecule pres.	0.000703^{**}	-0.000105	-0.00147^{*}
		$(4.71e{-}05)$	(0.000121)	(0.000720)
	Months of brand pres.	0.00159^{**}	0.000459^{*}	-0.000294
		(0.000106)	(0.000183)	(0.000794)
Practice	Num. of beneficiaries (100s)	0.00403^{**}	0.00375^{**}	0.0305^{**}
		(0.000206)	(0.000714)	(0.0113)
	Share with dual insurance	-0.0884^{**}	-0.0625^{**}	-1.523^{**}
		(0.00282)	(0.0211)	(0.257)
	Share female	0.156^{**}	0.00268	0.557^{*}
		(0.00945)	(0.0327)	(0.229)
Physician	Male	0.0292^{**}		
		(0.00201)		
	Years of experience	-0.000653^{**}		
		$(6.71e{-}05)$		
	Hospital affiliated	0.00358^{*}		
		(0.00177)		
	Internalists	-0.0375^{**}		
		(0.00310)		
	Gastroenterologists	0.116^{**}		
		(0.00338)		
Fixed Effects	Physician specialty	✓	✓	✓
	Prescription decile	✓		
	{brand, period}	✓	✓	✓
	{brand, physician}		✓	✓
R-squared		0.133	0.761	0.941
Observations		184,340	184,340	6,594

Notes: Linear probability models with 1(received payment) as dependent variable. Robust standard errors in parentheses. * Significant at the 5% level, ** Significant at the 1% level.

physician's patients treated with aminosalicylates. My Medicare Part D data does not allow me to observe individual patients' diagnosis, nor aggregate information (counts, ratios) about the myriad diagnoses of the physician's patients. It does, however, include data on the distributions of age, gender and race of each physician's patient population. For each physician, I estimate the size of the IBD patient population based on the demographic composition on her aggregate patient demographic characteristics.

I estimate the incidence rate of IBD using an auxiliary data set, the Medicare Health Outcome Survey (HOS). HOS surveys a random sample of Medicare beneficiaries, collecting (among other) information on chronic conditions of beneficiaries. I use the public use version of the survey data for 2013-2015 to estimate a probit model, where the dependent variable receives value if the Medicare beneficiary answered "yes" to the question "Has a doctor ever told you that you had Crohn's disease, ulcerative colitis, or inflammatory bowel disease?", and the regressors are fully interacted indicators for age groups (under 65, 65-74, 75 and over), race and sex. Estimation results are presented in table 10.

With probit coefficients at hand, I calculate the number of patients by each subpopulation described in table 10 for each Medicare Part D prescriber, and estimate the predicted number of patients who suffer from IBD.

7.2.2 Flexible Brand Effects

The model specified in equation (12) separates payments effects to *own-effect* (that is, the effect of a brand-related payment on the brand prescription) and class-effect. However, one could estimate a more flexible model, allowing for payments related to brand k to affect the prescription of brand j in a unconstrained manner. I estimate

$$\log\left(s_{itj}\right) - \log\left(s_{it0}\right) = \sum_{k \in J} \sum_{h=0}^{t} \delta_{t-h,k,j} d_{ihk} + \eta_{ij} + \eta_{tj} + \nu_{itj} \tag{13}$$

where $\delta_{t-h,k,j}$ captures the effect of payments related to brand k on the decision to prescribe drug j.

Estimation results are presented in table 11. Physicians who stop receiving payments related to Asacol HD are less likely to prescribe the brand by 20 percent. In turn, they are

Table 10: Probit Model: IBD Diagnosis in HOS Respondents

Indicator Interactions			
Age	Sex	Race	Coefficient
Under 65	Male	White	-1.519**
			(0.0133)
Under 65	Male	Nonwhite	0.0703**
			(0.0164)
Under 65	Female	White	0.147**
			(0.0172)
Under 65	Female	Nonwhite	0.444**
			(0.0152)
65-74	Male	White	-0.252**
			(0.0178)
65-74	Male	Nonwhite	-0.297**
			(0.0148)
65-74	Female	White	-0.0815**
			(0.0158)
65-74	Female	Nonwhite	0.0319*
			(0.0141)
75 and over	Male	White	-0.159**
			(0.0210)
75 and over	Male	Nonwhite	-0.262**
			(0.0156)
75 and over	Female	White	-0.0843**
			(0.0176)
75 and over	Female	Nonwhite	0.00773
			(0.0144)
Pseudo R-squared			0.02
Observations			779,709

Notes: Probit model estimation with 1(has IBD) as dependent variable. Robust standard errors in parentheses. * Significant at the 5% level, ** Significant at the 1% level.

likelier to prescribe Lialda, the newer Shire brand, by 14 percent. Physicians who stop receiving payments related to Canasa are less likely to prescribe Canasa by 4 percent, though coefficient is not significant. They are also less likely to prescribe Apriso (by 13 percent) and generic mesalamine (5 percent). For payments related to Apriso, I find reductions in the probability of prescribing several brands, but none are significant.

Table 11: Full Model Coefficients: Odds Ratios

		Brand Payments		
Molecule	Brand	Asacol HD	Canasa	Apriso
Balsalazide	Generic	1.01	0.99	0.95
		(0.05)	(0.06)	(0.04)
Mesalamine	Generic	1.00	0.95*	0.99
		(0.02)	(0.02)	(0.02)
	Apriso	1.04	0.87*	1.01
		(0.06)	(0.06)	(0.05)
	Asacol	0.93	0.97	0.99
		(0.04)	(0.05)	(0.03)
	Asacol HD	0.80**	0.99	0.96
		(0.04)	(0.07)	(0.05)
	Canasa	1.03	0.96	0.96
		(0.04)	(0.04)	(0.03)
	Delzicol	0.97	0.91	1.00
		(0.04)	(0.05)	(0.04)
	Lialda	1.14*	0.91	0.97
		(0.07)	(0.07)	(0.06)
	Pentasa	1.01	0.95	0.95
		(0.05)	(0.05)	(0.04)
Sulfasalazine	Generic	1.01	0.91	0.96
		(0.05)	(0.05)	(0.04)
	Generic (DR)	0.99	0.94*	0.99
		(0.02)	(0.03)	(0.02)

Notes: Estimation of the model detailed in equation 13. Using 387,288 observations. Robust standard errors in parentheses. For testing $H_0 = 1$: * Significant at the 5% level, ** Significant at the 1% level.