The Role of Information in Pharmaceutical Advertising:

Theory and Evidence

Kelli Marquardt and Conor Ryan

October 12, 2023

WP 2023-40

https://doi.org/10.21033/wp-2023-40

FEDERAL RESERVE BANK of CHICAGO

The Role of Information in Pharmaceutical Advertising: Theory and Evidence*

Kelli Marquardt[1] and Conor Ryan[2]

[1]Federal Reserve Bank of Chicago

[2]Pennsylvania State University, Department of Economics

October 12, 2023

Abstract

This paper theoretically and empirically examines the role of information in the practice of pharmaceutical detailing (promotional interactions between drug representatives and physicians). We start with a theoretical framework in which pharmaceutical firms target detailing visits to physicians who potentially learn about drug quality and prescribe it to their patients. We derive several predictions about the role of information in these visits, which we then test empirically using Medicare Part D prescriptions and pharmaceutical detailing visit data. We find there is little empirical evidence to support learning as a primary mechanism of detailing visits and, in fact, document strong evidence to the contrary.

Keywords: pharmaceutical advertising, physician learning

JEL Classification: I1, D8, L0, M3

*We would like to thank Abby Alpert and the participants of the American Society of Health Economists conference for valuable comments and suggestions. We also thank Sheikh Atiya Islam, Aryan Safi, Bea Rivera, and Cameron Deal for excellent research assistance. The views here do not represent those of the Federal Reserve Bank of Chicago or the Federal Reserve System. All errors are our own.

1 Introduction

Pharmaceutical firms often promote drugs through "detailing" in which drug representatives meet directly with physicians, typically over a meal. Existing economic literature has established that these detailing visits are successful in increasing targeted doctors' prescriptions of the intended drug (Agha and Zeltzer, 2022; Carey et al., 2021; Grennan et al., 2022).[1] While proponents contend that this marking practice provides valuable information (Hincapie et al., 2021), there is little evidence quantifying the extent to which physician responses are due to information provision rather than other aspects of traditional advertising, such as brand loyalty, reputation, or prestige, which are unrelated to patient benefits (Ackerberg, 2001).

In this paper, we use a model of physician decision making under uncertainty about drug quality and a model of profit-maximizing firms to make predictions about the role of information in detailing visits. We test the predictions of the model for eight large detailing campaigns and physician prescribing behavior in Medicare Part D. While we cannot rule out that physicians learn from detailing visits, we show there is little empirical evidence to support learning as a primary response mechanism and, in fact, document strong evidence to the contrary.

In the model, physicians respond to detailing visits through two mechanisms—learning about the drug and a direct, utility effect of advertising. The model implies four key predictions about the role of information exchange. First, the effect of detailing will be greater among physicians that are previously unaware of the drug's existence, i.e. did not consider it in their prescription decision. Second, physicians with less experience (more uncertain beliefs) will have greater increases in their prescriptions after a detailing visit. Third, physicians that are more pessimistic about a drug (lower mean of beliefs) will have greater increases in their prescriptions. And finally, repeated detail visits to the same physician will have diminishing returns from information. On the firm side, pharmaceutical manufacturers target their detailing visits to physicians in order to maximize a drug's total prescription volume. The optimal targeting strategy details the physicians with the greatest expected response in prescriptions. Thus, if information is a dominant mechanism in detailing visits, the physicians targeted for detailing will look similar to those predicted to have the greatest responses to information.

To test these predictions, we combine data on the universe of pharmaceutical detailing visits, compiled in the OpenPayments database by the Center for Medicare and Medicaid

[1] A related pharmaceutical promotion technique is direct-to-consumer advertising, which researchers have shown also leads to increased prescriptions (see, for example Sinkinson and Starc, 2018; Shapiro, 2022; Alpert et al., 2023).

Services (CMS), with physician-year level panel data on Medicare Part D prescriptions and patient characteristics from 2013 to 2019. We study new drugs released between 2014 and 2017 that (i) have an average of at least 10,000 detailing visits per year and (ii) are clearly indicated for a chronic condition observable in the Medicare data. There are eight drugs that meet these criteria: three to treat chronic obstructive pulmonary disease (COPD), three to treat diabetes, one to treat mental illness, and one to treat osteoporosis. To account for unobserved detailing endogeneity, we follow Grennan et al. (2022) and Larkin et al. (2017) in using data on the location of academic medical centers (AMC) with high conflict of interest (COI) scores as a source of plausibly exogenous variation in the propensity to receive a detailing visit, conditional on patient-mix and specialty.

First, we test whether the effect of detailing is greater among physicians that might be previously unaware of the drug. Physicians with no prior prescription history have large responses on the extensive margin and more modest but significant responses on the intensive margin—consistent with the hypothesis generated from the model. However, we cannot reject that this response is the same as for those physicians with prior experience prescribing the drug, suggesting that learning about the drug's existence is not the key mechanism driving physician response to detailing.

Next, we test whether physicians with less experience with and lower (pessimistic) beliefs about drug quality have greater responses to detailing. We measure physician experience using the volume of Part D prescriptions of a particular drug that a physician prescribed in the prior year. As a measure of physician mean beliefs about drug quality, we estimate each physician's prescription rate relative to a *benchmark* prescription rate, which we define as the patient-adjusted prescription share among "expert" physicians. Across all drugs in the sample, we find that more experienced physicians and over-prescribing (i.e. optimistic) physicians have greater responses to detailing. This directly contradicts the hypothesis generated by the model of learning and suggests that the other kinds of advertising effects may be more important in driving physician responses.

Finally, we test whether firms target physicians who would benefit most from learning about drug quality as motivated by the model. We estimate a targeting policy conditional on physician experience, physician mean beliefs, whether the physician was detailed in the prior year, and a set of controls for patient volume, physician specialty, and patient characteristics. We find very little evidence that is consistent with information as a dominant mechanism for detailing visits. For all drugs in the sample, firms are more likely to target physicians that have more prior experience with the drug. For five out of eight drugs, firms are more likely to detail over-prescribers, and only target under-prescribers for one drug in the empirical sample. We also find that firms dramatically favor revisiting previously detailed physicians

rather than potentially distributing information to new doctors.

Our results on physician responses to and firm targeting of detail visits are consistent, and both sets of results suggest that learning and information do not play a large role. Physicians with more experience and higher mean beliefs about drug quality respond more to detailing, and these are precisely the physicians targeted by the firms. This suggests that it is likely that other effects of advertising—brand loyalty, prestige, reputation, etc.—are playing a substantial role in detailing responses, and firms repeatedly target those physicians which they've identified as receptive to this kind of advertising. We demonstrate in a discussion section that a model with these kinds of effects can easily explain the data patterns we present in the main empirical section of this paper.

Related Literature

Our paper contributes to a large literature on pharmaceutical advertising. Literature studying the effects of direct-to-consumer advertising shows these ads to be effective in increasing the demand for a particular drug (Sinkinson and Starc, 2018; Shapiro, 2022; Alpert et al., 2023). In many settings, advertisements to consumers can generate large welfare gains by overcoming other kinds of barriers that lead to inefficiently low prescription drug demand or adherence.

More specifically, there is a growing literature that studies advertising to physicians, i.e. pharmaceutical detailing. The positive effect of pharmaceutical detailing on prescription demand has been explored in the economics, marketing, and management literatures. Some that are most related to our study include: Agha and Zeltzer (2022); Carey et al. (2021); Grennan et al. (2022); Manchanda and Chintagunta (2004); Ching and Ishihara (2012); Shapiro (2018); Huang et al. (2019).

A key element of this work is the role of information and learning in physicians' responses to detailing, both theoretically and empirically. From a modeling perspective, we combine elements from various literatures including physician learning about unobserved drug quality (e.g., Crawford and Shum, 2005; Coscelli and Shum, 2004; Narayanan and Manchanda, 2009), persuasive vs informative effects of advertising (e.g., Ackerberg, 2001; Anand and Shachar, 2011) , and decision-making under uncertainty more broadly. Empirically, the small subset of studies that examine information in physician response to detailing have mixed results. For example, Shapiro (2018) finds evidence that detailing visits likely helped inform physicians about positive antipsychotic side effect profiles. Huang et al. (2019) show that detailing visits actually *reduce* prescriptions for contraindicated patients in support of their "informative detailing hypotheses," at least in the context of statins. This may not hold in the market for anticoagulants, however, as Agha and Zeltzer (2022) show detailing visits

increase prescriptions for both recommended and non-recommended patients. Our paper expands on this literature to study physician and firm behavior across a number of the largest detailing campaigns surrounding new drug entrants. While we cannot rule out that physicians do learn from detailing visits, our findings suggest that it is not a key mechanism in the responses to detailing visits.

The second key contribution of this paper is the inclusion of firm-side targeting. While existing research recognizes that physicians are endogenously detailed and use physician fixed-effects to control for this selection (most recently Carey et al. (2021) and Agha and Zeltzer (2022)), the underlying reason for this selection is not emphasized. Grennan et al. (2022) find that pharmaceutical firms selectively detail physicians with the highest expected response to detailing (as we emphasize in our theoretical model in Section 2.2). Further, the authors show that in the case of cardiovascular drugs, these targeted doctors are also those that would have otherwise been below-average of the drug. Our paper directly studies what the targeting policies of firms indicate about the role of information for new entrants across multiple drug classes. In contrast, we find that firms are more likely to target experienced and over-prescribing physicians.

The rest of the paper is structured as follows. In the next section, we provide institutional details on pharmaceutical marketing which then leads into our theoretical framework. In describing the model, we highlight the role of information in both physician response to detailing and pharmaceutical firm targeting, respectively. In Section 3, we introduce the drugs included in our empirical sample, describe the different data sources, and present data patterns that connect our theoretical model. Section 4 summarizes our empirical specifications and results. We discuss alternative models and explanations of data patterns in Section 5 and finally, Section 6 concludes.

2 Setting & Theoretical Framework

In the United States, advertising to physicians is an integral part of prescription drug marketing strategies. Advertising to physicians can take the form of honoraria for speaking engagements, sponsored conferences and continuing education seminars, free drug samples, or the focus of this paper, visits to physician offices, i.e. detailing visits. These visits typically take place over the course of a meal in which a representative of the drug manufacturer speaks with the physician about the drug and provides informational or marketing materials. In 2019, the drug and medical device industry spent $246 million on 9.4 million meals for physicians. This comprised about 12% of all payments to physicians, excluding royalties,

and represents the advertising channel that reaches the most physicians by far.[2]

Pharmaceutical manufacturing firms have been using this practice to market drugs to physicians since the mid-century, and its practice has scaled up in recent decades with the rise of prescription drug revenues. Firms typically collect via subsidiaries or purchase detailed information on physician prescription behavior and case mix demographics in order to organize and target their detailing campaigns (Manchanda and Chintagunta, 2004).

While the practice has been common for a long time, it has recently drawn more government attention over concerns that detailing visits might be compromising objective decision making by physicians (Guo et al., 2020). One result has been mandated transparency on the relationships between pharmaceutical firms and physicians, which is where the data for this project originates.

Before moving to the empirical section of this paper, we first present a theoretical framework of physicians and drug manufacturing firms. First, we illustrate a stylized model of physicians that write prescriptions for their patients based on preferences and beliefs about the quality of a drug. Detailing visits may influence physicians both directly via their preferences or through their beliefs about drug effectiveness for their patient set. Second, we write a model of drug manufacturing firms that decide which physicians to target for detailing visits. The model makes clear predictions about the role of information exchange in detailing visits (both physician response and firm targeting), which we then proceed to test empirically in the data.

2.1 Physician Prescribers

Physician i receives indirect utility u_{ip} from writing a prescription for a patient p. To model the role of detailing visits, we express this utility as a function of detailing $D \in \{0, 1\}$ such that $u_{ip}(D)$ is a sum of three components: a direct effect of detailing, θ_i, the mean of beliefs about drug quality, $\mu_{ip}(D)$, and variance of beliefs about drug quality, $\sigma^2_{ip}(D)$. For a particular physician, deciding whether to prescribe a particular drug to a particular patient, we write:

$$u_{ip}(D) = \theta_i D + \mu_{ip}(D) - \psi\sigma^2_{ip}(D), \tag{1}$$

where $D \in \{0, 1\}$ is an indicator of whether the physician is detailed and ψ relates to the physician's risk aversion. The physician's beliefs, μ and σ, are functions of whether or not the physician is detailed, with $D = 1$ representing posterior beliefs after potentially learning

[2]For comparison, the advertising/payment category with the next largest reach is travel and lodging. The drug and medical device industry paid covered these expenses for only 630 thousand physicians in 2019.

from a detailing visits. In Appendix A, we show how this utility framework can be derived from a model of Bayesian physicians with constant absolute risk aversion.

The physician may instead choose not to prescribe the drug, and pursue some other treatment. We consider all other potential treatments to be the outside option, O, and normalize their utility to 0. As such, u_{ip} can be considered to be the utility relative to the next best option.

When a physician receives a detailing visit, the utility from prescribing in a given situation is influenced through each of these three terms. The first term captures the direct effect of the visit, through θ. This captures "brand" effects of advertising, such as perceptions of prestige or brand loyalty. The second term captures the effect of a detailing visit on the physician's average belief of drug quality, and the third term captures the effect of a detailing visit on the physician's uncertainty about drug quality.

In addition to beliefs about the utility of the drug, the physician has a consideration set $\Omega_i \in \{(O, d), (O)\}$. The consideration set is simply one of two possibilities: a set that includes the drug d and the outside option O, or a set that includes only the outside option. This represents the possibility that, without additional information, some physicians may be unaware that the drug is available to prescribe.

Let ϕ_i denote the probability that the drug is in the physician's consideration set, and let P_i denote the probability that a physician will prescribe the drug to one of their patients. The physician can only prescribe if he/she knows about the drug, and each probability is conditional on whether or not the physician is detailed.

$$P_i(D) = \phi_i(D) \times Pr(u_{ip}(D) > 0)$$

Let ΔP_i describe the effect of a detailing visit on the probability that a physician prescribes the drug to a patient.

$$\Delta P_i = \phi_i(1) Pr(u_{ip}(1) > 0) - \phi_i(0) Pr(u_{ip}(0) > 0)$$

Role of Information

The purpose of this stylized model is to show intuitive predictions for the role that information plays in the effect of detailing visits on physician prescribing behavior. Their are two channels through which information provided by detailing visits can affect prescriptions.

The first information channel is spreading the word about the existence of the drug. Because the most fundamental purpose of the detailing visit is to inform physicians about the existence of the drug, we assume that $\phi_i(1) = 1 > \phi_i(0)$. Then, as long as $u_{ip}(1) \geq u_{ip}(0)$,

we have $\Delta P_i \geq 1 - \phi_i(0)$. In words, the effect of detailing on prescribing is positive but decreasing in prior awareness of the drugs existence, under the condition that utility of prescribing is weakly increasing in detailing.[3]

Given this implication, we should expect to see two things in the data if awareness among physicians prior to detailing is low. First, we should see an effect of detailing on the extensive margin of prescribing to *any* patients. Second, the effect of detailing should be larger on physicians that have not prescribed the drug in the past, i.e. those with $\phi_i(0) < 1$.

The second information channel is communicating the drug match quality for a physician's patients. Suppose the mean and variance of the physician's prior beliefs are given by μ_0 and σ_0^2, respectively. If a physician is not detailed ($D = 0$), then there is no updating. If they are detailed ($D = 1$), then the information provided by the detailing rep is a noisy signal about the true quality: $\tilde{D} \sim N(\mu_{true}, \sigma_D)$. As a result of the visit, the physician will update the mean and variance of their beliefs as follows:[4]

$$\mu_{ip}(D=1) = \mu_{0ip} + \underbrace{\frac{\sigma_{0ip}^2}{\sigma_D^2 + \sigma_{0ip}^2}\left(\tilde{D} - \mu_{0ip}\right)}_{\text{Belief Update}} \tag{2}$$

$$\frac{1}{\sigma_{ip}^2(D=1)} = \frac{1}{\sigma_{0ip}^2} + \underbrace{\frac{1}{\sigma_D^2}}_{\text{Belief Update}} \tag{3}$$

Now, had the physician *not* received a detailing visit, then her beliefs would not update and utility would be $u_{ip}(0) = \mu_{0ip} - \psi\sigma_{0ip}^2$ rather than the utility $u_{ip}(1)$ which includes the updated mean (equation 2) and variance (equation 3) denoted above.

Recall that conditional on the drug being in the physicians information set, the effect of detailing is proportional to $u_{ip}(1) - u_{ip}(0)$. Therefore, we can compare the above updated beliefs in equations (2) and (3) relative to prior beliefs (μ_{0ip} and σ_{0ip}^2) to guide predictions about the indirect effect of detailing on physician utility via their Bayesian learning.[5]

There are several predictions that follow from this comparison. First, the effect of detailing is increasing in the variance of the physician's prior, σ_{0ip}^2. This implies that the detailing effect should be larger for physicians with less experience with/higher uncertainty about the

[3]The condition that utility from prescribing the drug is greater with detailing than without is important but not very restrictive. Conditional on what they can observe, drug manufacturers would prefer not to detail physicians for whom this condition is violated, i.e. those that would get negative utility from detailing visits. We can safely restrict our attention to the set of physicians for which this is true. The firm's targeting decision is discussed in more detail in the following section.

[4]In Section 5, we consider the implications of a model of learning in which physicians are not necessarily Bayesians in the manner specified here.

[5]See Appendix A for additional details and derivations.

drug (high σ_0). Second, the effect of detailing on mean beliefs depends on the mean of the prior, μ_{i0p}. Assuming that detailing signals must be accurate of true quality on average (i.e. $E[\tilde{D}] = \mu_{true}$), this implies that physicians who are more pessimistic about a drug ($\mu_{0ip} << \mu_{true}$) will have greater positive response to detailing visits, and vice versa. And finally, because the effects of information are persistent, the returns to repeated detailing visits should be diminishing.

In conclusion, this model implies four key predictions about the role of information in physician responses to detailing:

1. The effect of detailing will be greater if detailed physicians are previously unaware of the drug's existence, i.e. did not consider it in their prescription decision.
2. Physicians with less experience (more uncertain beliefs) will have greater increases in their prescriptions after a detailing visit.
3. Physicians with lower mean beliefs (pessimistic about drug quality) will have greater increases in their prescriptions.
4. Repeated detail visits to the same physician will have diminishing returns from information.

2.2 The Firms

We now pair the above physician learning and decision-making process with a model of pharmaceutical firms who use detailing campaigns to maximize the prescription profit of a particular drug, net of the cost of the campaign. The firm will maximize profit by targeting the physicians who will respond to detailing with the greatest magnitude of additional prescriptions, and detail all physicians that exceed a threshold given by the marginal cost.

More formally, the drug manufacturing firm decides which physicians, i, to detail (D_i) for their particular drug. Each filled prescription generates profit π, and the cost of detailing is given by some convex function $C()$.[6] The firm observes the set of potential prescribers and their volume of patients that could potentially be a candidate for the drug, V_i.[7] The profit of the firm is given by

$$\Pi = \sum_i \pi V_i P_i(D_i) - C(\sum_i D_i). \tag{4}$$

[6]There are reasons why π might not be constant in the detailing effort. There could be economies or diseconomies of scale in production, and additional demand due to detailing may lead to greater markups, as in Grennan et al. (2022). As long as profit depends on total prescriptions rather than physician-specific prescriptions, the predictions from this section are robust.

[7]The firms can measure this using prior prescriptions of drugs with a similar class. In our empirical exercise, we are going to measure it using data on disease prevalence among the physician's patient population.

The firm will allocate its detailing visits to the physicians with the greatest expected response in terms of total prescriptions. In the simplest case where the cost of detailing is constant, $C(\sum_i D_i) = c \sum_i D_i$, physicians will detail all physicians that satisfy

$$\underbrace{\pi V_i \big(P_{i,D=1} - P_{i,D=0}\big)}_{\text{Additional Profit from Detail Visit}} > c \tag{5}$$

Conditional on total relevant patient volume, firms will be more likely to detail physicians that have greater responses in their prescription behavior, i.e. those with larger ΔP_i.

Firms have potentially more complex detailing costs. But for many kinds of cost functions, the set of firms that physicians that firms decide to detail will all have a greater predicted response than every physician in the set that is not detailed. One possibility that could violate this result is if the cost of detailing visits are physician specific, perhaps due to local travelling or transportation costs. In our empirical exercise, we control for geographic location in order to address this possibility.

Role of Information

The role of information in the model of the firm is analogous to that of the model of physicians. We can translate all of the physician model predictions about which physicians will respond greatest to detailing into predictions about who the firm should detail. The presence of these information channels will make it more likely that, conditional on volume, a firm targets physicians that:

(i) are previously unaware of the drug (a low ϕ)
(ii) have less experience with the drug (a high σ_0)
(iii) have low prior beliefs about the drug (a low μ_0)
(iv) have not been detailed in the past.

However, there is an important distinction in the role of information in firm behavior relative to those in Section 2.1. The predictions about the role of information physician prescription behavior may be present if information plays *any* role in the effect of detailing visits on prescription behavior. In contrast, the predictions about the role of information in firm targeting decisions concerns whether information plays a *dominant* role, relative to the direct marketing effects of detailing.

The "warm glow" effect of detailing—θ in the physician's prescribing utility—may dominate any indirect effect of detailing on beliefs that we describe in section 2.1. Therefore, while the behavior of physicians can indicate whether these information channels are present,

the behavior of the firm can help to provide insight into the importance of these channels relative to other kinds of marketing effects.

3 Data

3.1 Data Sources

Our empirical analysis combines information from three data sources: (1) CMS OpenPayments database of pharmaceutical detailing visits, (2) Medicare Part D annual prescriptions and patient demographics, and (3) archived American Medical Student Association (AMSA) scorecards.

Detailing

The OpenPayments database reports the universe of detailing visits and payments from drug manufactures to physicians, federally mandated in 2013 and maintained by CMS. The data contain the date of the visit, the nature of the payment (e.g. a purchased meal), the monetary value of the payment, the names of up to five products that were associated with the transfer, and the name and address of the physician. We restrict our focus to interactions that take place over a meal (identified as in-kind payments of food and beverage) and take place between January 2015 and December 2019. The interquartile range of the value of all meals in the data is $11 to $19. We refer to these interactions as detailing visits.

Medicare Part D

The Center for Medicare and Medicaid Services also maintains data on prescriptions written for Medicare Part D, a government sponsored prescription drug program for the elderly and disabled. The data contain the total number of prescriptions filled for each drug during a year by physician, denoted by their National Provider Identifier (NPI). The data also contain information on the physician's speciality, the total number of Part D beneficiaries seen by the physician during the year and patient-mix demographics, including race, gender, age, average risk factors, and the fraction of patients that are diagnosed with each of a set of chronic conditions. These data are missing wherever they would identify a group with less than 11 individuals, and we drop any physicians that see fewer than an average of 100 Medicare beneficiaries per year.

We match the prescription data to the OpenPayments data using a sequential match on physician name only, name and state, name and city, and finally name and zipcode. In each

match, we keep only physicians that are uniquely identified in both the OpenPayments data and the universe of physicians with registered NPI numbers. Through this process, we are able to identify the NPI for 94% of physicians in the OpenPayments data and 96.2% of the total number of payments.

Using this data source, we construct a physician-year panel with information on number of detailing visits in total and by drug. We then merge this with the yearly Medicare Part D prescribing data, resulting in a physician-year panel with both detailing visits and prescription claims by drug, in addition to patient mix and physician characteristics.

AMSA Scorecards

The AMSA collects information on conflict of interest (COI) policies for member academic medical centers (AMC). The AMSA give each center a score in a range of fields governing different aspects of COI policies. The scores range from 1 to 3, with 3 being the most restrictive with respect to potential conflicts. We have data on these information for 2014 and 2016. We follow Grennan et al. (2022) in creating a summary measure by summing the score across all the fields and taking the average across the two years. We consider an AMC to have a strong conflict of interest policy if their total score is greater than 30, the median summary score.

3.2 Sample Selection

We aim to study detailing campaigns of branded drugs that enter the market between 2015 and 2017, which allows us at least two years of post-entry data. We define market entry as the first year in which the drug has positive prescription rates and positive detailing visits. We consider all new drugs in this period that have at least an average of at least 10,000 detailing visits per year and treat one of a set of observable chronic conditions in the Part D prescription data. In total, there are 16 drugs that meet this criteria: 6 diabetes medications, 3 medications for chronic obstructive pulmonary disease (COPD), 3 medications for hyperlipidemia and chronic heart failure, 2 medications for mental health conditions such as schizophrenia and bipolar disorder, 1 Alzheimer's disease medication, and one medication for osteoporosis.

Next, we eliminate drugs that are specialized to unobservable subsets of the patients with the particular chronic illness in order to reduce measurement error in the share of patients to which the drug is prescribed. For instance, Repatha is used to treat adults with hyperlipidemia that are already on diet or statin therapy, and the drug to treat Alzheimer's, Namzaric, is only to be used in conjunction with memantine hydrochloride and donepezil

hydorchloride. The 8 remaining drugs in the sample are presented in Table 1 along with the chronic condition they treat, the drug manufacturer, and the entry year.

Table 1: Drugs in Full Empirical Sample

Drug Name	Chronic Condition	Manufacturer	Entry Year
Anoro Ellipta	COPD	GlaxoSmithKline	2014
Stiolto Respimat	COPD	Boehringer Ingelheim	2015
Bevespi Aerosphere	COPD	AstraZeneca	2017
Toujeo	Diabetes (I & II)	Sanofi	2015
Tresiba	Diabetes (I & II)	Novo Nordisk	2016
Basaglar	Diabetes (I & II)	Eli Lilly and Company	2017
Tymlos	Osteoporosis	Radius Health	2017
Vraylar	Schizophrenia+	AbbVie	2016

Note: This table displays the 8 drugs in the main estimation sample described in Section 3. For each drug, we list the condition that it treats, the manufacturing firm, and the entry year, i.e. the first year that the drug could be prescribed to patients.
+: Vraylar treats other mental illness such as bipolar disorder in addition to schizophrenia.

In order to balance the selection of a reasonably comparable (and smaller) sample with the goal of a broad survey of detailing campaigns across many drugs and manufacturers, we perform all of the main analysis on the 8 more specialized drugs as well. We refer to these drugs as the *extended sample*. In Appendix Table C1, we present the same descriptive information for this set of drugs as well as the unobserved indications that make their use more challenging to measure.

Table 2: Summary Statistics

Drug	Scripts (thous.)	Ever Prescribe	Rx Share | Prescribe	Detail Visits (thous.)	Ever Detailed	Ever Prescribe | Detailed
Anoro	3317	0.18	0.015	452	0.13	0.55
Stiolto	779	0.05	0.009	219	0.09	0.27
Bevespi	145	0.02	0.008	195	0.06	0.12
Toujeo	2107	0.15	0.011	364	0.13	0.50
Tresiba	2142	0.14	0.014	546	0.15	0.45
Basaglar	1488	0.18	0.012	166	0.10	0.37
Tymlos	37	0.01	0.009	32	0.03	0.12
Vraylar	149	0.05	0.023	84	0.07	0.31

Note: This table shows the summary statistics for each drug in our sample and the corresponding sample of physicians. In order from left to right, columns correspond to: the total number of prescriptions across the sample time period, the share of in-sample physicians that ever prescribe the drug, the prescription share of those that do prescribe the drug, the total number of detailing visits, the share of physicians in the sample that are detailed, and the share of physicians that ever prescribe the drug among those who were ever detailed.

For each drug, we select a sample of relevant prescribing physicians. In order to appear

in the sample, the physician must have an average of at least 100 Part D beneficiaries throughout the sample period, write an average of at least 100 part D prescriptions per year, and be a member of one of the top prescribing specialties.[8] Additionally, in the analysis of physician responses, we restrict the sample to physicians that live within 300 kilometers of an AMC. Ultimately, we will use this distance as a source of exogenous variation in detailing probability, and we want to restrict the sample to a group of physicians for which the instrument has a plausible effect on the propensity to be detailed. This restriction removes roughly 6% of the physicians across all drugs from the sample. Table 2 provides additional summary statistics on prescriptions and detailing for each drug.

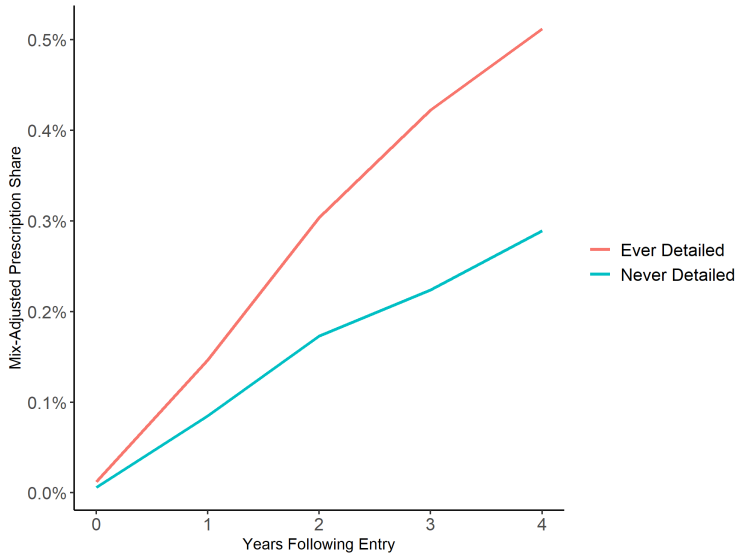
3.3 Motivating Data Patterns

In this section we show three data patterns that motivate the analysis that follows. First, the prescription share of a particular drug is greater and increases faster among physicians that receive detailing visits from the manufacturer, even after adjusting for differences in patient-mix across physicians. Figure 1 shows the average prescription share for all drugs in the sample, divided by physicians that have never been detailed and those that are detailed at least once throughout the whole sample period. By 3 years after entry, the prescription share among ever detailed physicians is more than double the share among physicians that never receive a detailing visit, again conditional on differences in patient mix.

Second, manufacturing firms prefer to repeatedly detail the same set of physicians rather than detail as many physicians as possible. In Figure 2, we show the average allocation of detailing visits across time and physicians normalized by the total number of visits in the first year of entry. Detailing campaigns often ramp up the number of visits following the initial year of entry and focus on making repeat visits to previously detailed physicians. By 2 years after entry, only a small fraction of total detail visits are allocated to physicians that have never been detailed, despite detailing only a small fraction of doctors overall (Table 2).

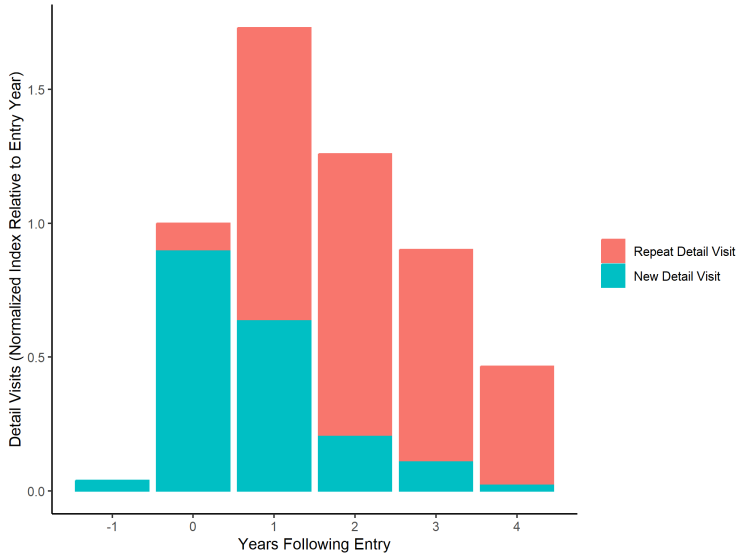
[8] We define the top prescribing specialties by adding specialties until we account for 95% of all the drugs prescriptions.

Figure 1: Mix-Adjusted Prescription Share Grows Faster Among Those Detailed



Note: Physicians that ever experience a detailing visit prescribe more of the target drug, and the prescriptions increase faster following entry. This figure shows the mean patient-mix adjusted prescription share of physicians that are ever detailed and never detailed, averaged across all drugs in the sample and weighted by the total supply of the drug.

Figure 2: Most Detail Visits are Repeat Visits after Initial Entry

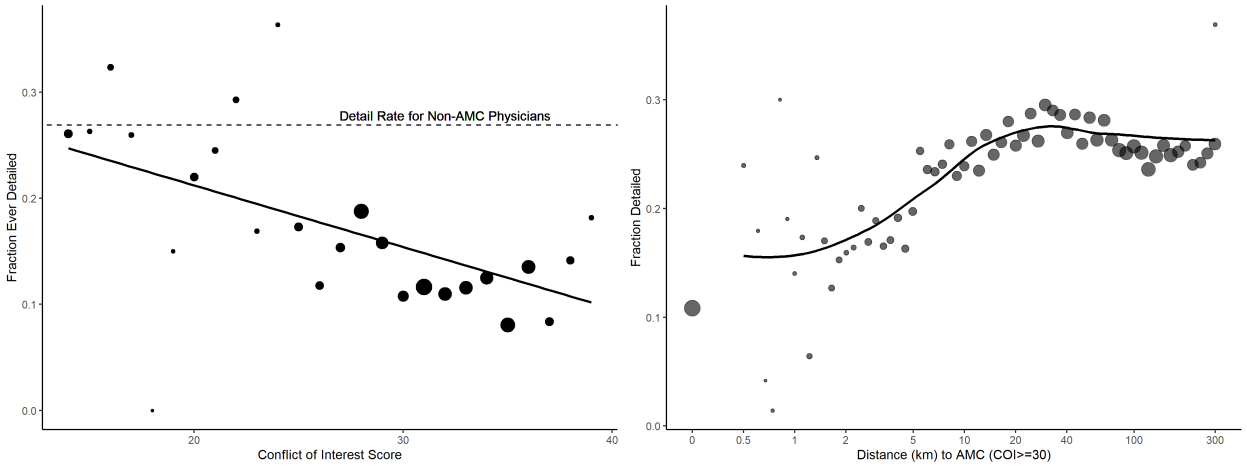


Note: Detail visits ramp up following the entry of the target drug and are primarily targeted towards the same set of physicians. This figure shows the trend in detail visits, normalized to the total number of visits in the year of entry and averaged (unweighted) across all 8 drugs in the sample. In each year, we group visits by those to physicians that have been detailed at least once before (Repeat Detail Visit) and those that have not yet been detailed (New Detail Visit).

And finally, we show that the conflict of interest scores are an important predictor of which physicians are ultimately detailed. In Figure 3a, we group physicians by the conflict of interest score given to the AMC at their practice address. The probability that a doctor

ever receives a detailing visit for any drug in the sample is negatively correlated with the AMC score, and the average rate of detailing among physicians that do not practice at any AMC is greater than those that do.

Figure 3: Fewer Doctors are Detailed near High COI Institutions



(a) High COI Institutions Detailed Less (b) Detailing Probability Increases with Distance

Note: Physicians that work at or near an AMC that has a high COI score are less likely to be detailed. Panel (a) shows the fraction of physicians detailed that work at an AMC (matched by address) of each COI score. Dotted line corresponds to the detail rate for physicians with work addresses not linked to an AMC. Panel (b) shows that the fraction of physicians detailed increases with the (log) distance to the AMC, measured by zip code centroids. In each plot, the size of the dots are proportional to the number of physicians represented in the relevant bin.

However, it is likely that there are some spillovers from the local AMC to other non-AMC physicians in the area, especially if physicians have practice agreements with the hospitals that we may not observe, or if detailing reps find it less worthwhile to travel to an area where the main hospital is excluded. In Figure 3b, we show that the probability of being detailed increases with the distances from the zip code that contains the AMC. The distances are computed using the centroids of the AMC zip code and the zip code of the physician's practice address. We only include AMCs that have a COI score of at least 30, where the effect on detailing seems to be most significant. In the empirical analysis that follows, we use this distance as plausibly exogenous variation in detail visit propensity.

4 Empirical Tests for Information

In this section, we use the analytical sample described in Section 3 to test predictions of our theoretical model and quantify the importance of information exchange in pharmaceutical detailing. We estimate both physician prescription response to detailing visits and factors that influence firm detailing efforts. To quantify the role of information, we test for differences

in physician response and/or firm targeting according to physician *experience with* and *beliefs about* the target drug.

4.1 Physician Prescription Response

4.1.1 Empirical Specifications

The goal of our analysis of physician behavior is to compare patterns in the effect of detailing visits on prescriptions to predictions from the model in Section 2. We apply a simple, linear model for each drug in our sample and each outcome of interest.

$$y_{idt} = \beta_d D_{idt} + \gamma_d X_{it} + \lambda_{dt} + \epsilon_{idt}, \tag{6}$$

We are concerned with two potential outcomes representing the extensive and intensive margins of the physician's prescription decision. The first is a binary outcome of whether the physician i writes any prescriptions of the drug d during the year t, $y_{idt} = RxPos_{idt} \in \{0, 1\}$. The second is the percent of patients seen by physician i with the relevant chronic condition that are prescribed the drug d in year t, measured in percentage points: $y_{idt} = RxShare_{idt} \in [0, 100]$. $D_{idt} \in \{0, 1\}$ indicates whether physician i received any detailing visit for the target drug in year t. The vector X_{it} includes both patient-mix composition controls and an indicator for whether physician i is a specialist relevant to the treated condition (e.g. a pulmonologist in the case of drugs treating COPD)[9]. We also include year fixed effects, λ_{dt}. Each regression is estimated separately for each drug d, and standard errors are clustered at the physician level.

Because firms have an incentive to target their detailing visits towards those that are expected to have the greatest responses, we expect the detailing visits D_{idt} to be correlated with things about the physician's prescriptions that we cannot observe, ϵ_{idt}. Similar to Grennan et al. (2022), we use the distance between the physician's practice zip code and the nearest AMC with a conflict of interest score greater than or equal to 30 as an instrument for detailing visit propensity.[10] Because some of our specifications are linear probability models, we use a discretized version of the instrument to allow for non-linearities in the first stage. This is similar to a non-parametric instrumental variable approach and allows the data to

[9]Our patient-mix controls include the average age, the average risk score, fraction of patients that are male, white, and dual-eligible for Medicaid, and the fraction of patients that have been diagnosed with one of the following: heart failure, chronic kidney disease, chronic obstructive pulmonary disease, depression, diabetes, hyperlipidemia, hypertension, ischemic heart disease, and rheumatoid arthritis/osteoporosis. For a particular drug specification, we explicitly exclude the disease control that the drug itself treats as this is included in the construction of market size.

[10]In addition to the standard linear IV, we have also estimated many of the results that follow using a control function approach and marginal treatment effects, and we arrive at qualitatively similar findings.

discipline the appropriate bounds on the probability of being detailed. We bin distance in 5 kilometer increments up to 50 kilometers away from an AMC, with a separate bin for physicians in the same zipcode as an AMC. The exact specification of the bin size has little quantitative effect on the results.

Next, we estimate versions of this baseline model that allow the effect of detailing to vary with measures of experience and beliefs. Specifically, we estimate the following two specifications:

$$RxShare_{idt} = \left(\beta_d + \beta_d^{exp} Experience_{id,t-1}\right) D_{idt} + \gamma_d X_{it} + \lambda_{dt} + \epsilon_{idt} \tag{7}$$

$$RxShare_{idt} = \left(\beta_d + \beta_d^{bel} Beliefs_{id,t-1}\right) D_{idt} + \gamma_d X_{it} + \lambda_{dt} + \epsilon_{idt} \tag{8}$$

Using Equation (7), we test whether more experienced physicians have smaller responses to detailing (see prediction # 2 in section 2.1). In most specifications, our measure of $Experience_{id,t-1}$ is prior year supply, i.e. the total amount of annual prescriptions associated with the target drug that were written by physician i in the previous year.

Using Equation (8), we test whether physicians that have lower mean beliefs about the drugs' quality have greater responses when detailed and given new information (see prediction # 3 in section 2.1). To do so, we construct a measure of physician prior beliefs using the following two step procedure. See Appendix B for additional details.

1. Determine "true" drug quality match as a function of patient-mix controls: $\widehat{Q}_{it}(X_{it})$. This value is based on estimated coefficients from a benchmark prescription share model of experts (physicians at high COI Academic Medical Centers in 2019) used to predict what the non-expert physician prescription share *should* be given their yearly patient-mix and specialty.

2. Back out physician-year prescription share residual $Belief_{idt} = (RxShare_{it} - \widehat{Q}_{it}(X_{it}))$. We define pessimistic beliefs as those who are prescribing below true drug quality match benchmark. In other words, pessimistic physicians are those with $Belief_{id,t-1} < 0$.

In these specifications, we use the same exogenous variable/instrument for detailing as before: the distance to the nearest AMC with a high conflict of interest score. In this case, we also instrument for the interaction using the instrument times the lagged experience or lagged belief measure. Because the experience and prior belief measures are only defined for physicians with some prior prescriptions, we estimate these results only for physicians that have some prior history of prescribing the drug.

4.1.2 Results

Awareness

We start by testing a key mechanism for informative detailing: awareness of the drug. As outlined in Section 2.1, detailing may have large informative effects if physicians are broadly unaware of a particular drug and detailing adds a new (and potentially better) option to their consideration set. The model makes two predictions about physician responses in this dimension. First, detailing will have an effect on the extensive margin of whether or not a physician makes any prescriptions for the drug. And second, the effects of detailing should be greatest among physicians that have never prescribed the drug before. Accordingly, we estimate the effect of detailing on both the extensive and intensive margin among physicians that do or do not have prior prescription history with the drug.[11]

Table 3 presents the point estimates and standard errors for each estimation. Figure 4 provides a visualization of these results.[12]

Figure 4a shows that the extensive margin responses (i.e. $y_{idt} = RxPos_{idt}$) to detailing are significant. For most drugs in the sample, physicians with no prior prescription history are between 13 and 36 percentage points more likely to prescribe the drug after detailing. This finding is consistent with the idea that detailing increases the awareness of a drug. We find some limited evidence that physicians with prior prescription history have less extensive margin response to the drugs, but for five out of eight drugs in the sample, we cannot reject that the responses to detailing are the same.

Figure 4b shows the intensive margin responses (i.e. $y_{idt} = RxShare_{idt}$). Physicians with no prior prescription history have significant but modest responses in the share of patients to which they prescribe the drug. Detailing leads to an increase by about 0.1 to 1 percentage points in the share of patients they prescribe the drug. For one drug in the sample, we find evidence that physicians with prior prescribing history have a *greater* intensive margin response than those with no prior prescribing history. But the confidence intervals for most other drugs include both no effect and the same response as the group with no history.

[11] We characterize "no prescription history" as having no prior prescriptions in the Medicare Part D data. While it is possible that some of these physicians have prescribed the drugs to non-Medicare patients, as long as some of these physicians do not have experience with the drug, this group is *less* aware than the experienced group.

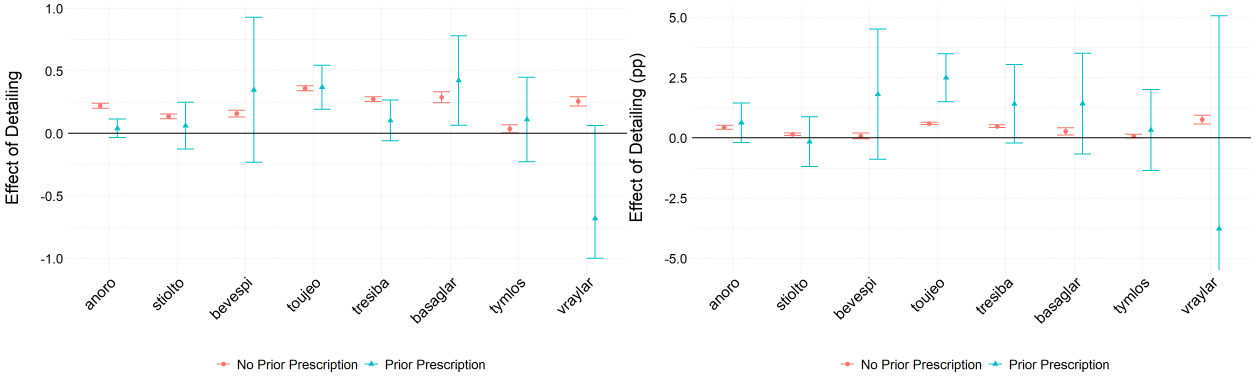
[12] Appendix Table C2 presents the physician response results for the extended sample. In general, the results are qualitatively similar. We find smaller extensive margin responses and a negative response for one drug. However, since these drugs have important patient-level indications that we cannot observe in the aggregate data, we are hesitant to place much interpretation on these results.

Table 3: Physician Response to Detailing

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Effect of Detailing on Any Prescription of Drug								
No Prior Prescriptions	0.221*** (0.011)	0.136*** (0.010)	0.158*** (0.014)	0.361*** (0.010)	0.274*** (0.009)	0.288*** (0.022)	0.036** (0.016)	0.256*** (0.019)
Prior Prescriptions	0.040 (0.038)	0.061 (0.095)	0.348 (0.296)	0.369*** (0.090)	0.104 (0.083)	0.422** (0.183)	0.111 (0.172)	-0.680* (0.378)
Panel B: Effect of Detailing on Prescription Share								
No Prior Prescriptions	0.438*** (0.042)	0.145*** (0.026)	0.079 (0.061)	0.598*** (0.026)	0.482*** (0.030)	0.271*** (0.077)	0.070* (0.039)	0.756*** (0.093)
Prior Prescriptions	0.625 (0.417)	-0.157 (0.527)	1.813 (1.377)	2.492*** (0.510)	1.410* (0.832)	1.422 (1.067)	0.324 (0.856)	-3.764 (4.505)

Note: Physicians without any prior prescription history respond to detailing. Each entry in the table corresponds to a 2SLS coefficient estimate on "Detail" in separate regressions. Each column contains the estimates for a particular drug. Panel A contains the estimates of the extensive margin estimation of whether or not a physician prescribes any of the drug in a given year. Panel B contains estimates on the effect of detailing (in percentage points) on the share of patient-days that are prescribed the drug during the year. The first row of each panel corresponds to physicians with no prior history prescribing the drugs in the data and the second row corresponds to physicians with observed prior prescriptions. Each estimation includes controls for year, specialty, patient-mix. Statistical significance is based on clustered standard errors at the physician level, with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 4: Physician Response to Detailing



(a) Any Prescription (b) Prescription Share

Note: Physicians without any prior prescription history respond to detailing, but there is little/no evidence of larger response compared to those with prior prescriptions. This figure plots the results in Table 3. Panel (a) displays the 2SLS estimates for the extensive margin response—additional probability of prescribing the drug to any patients—for physicians with and without prior prescription history. Panel (b) displays the 2SLS estimates for the intensive margin response—additional share of patient-days that are prescribed the drug, measured in percentage points—for the same sets of physicians. Both panels show the 95% confidence intervals around the point estimates.

Taken together, we find some evidence that drug awareness plays a role in the physician response to detailing. On one hand, we show that physicians without prior prescription

history with the drug (a measure for unawareness) do have substantial responses to detailing on both the extensive and intensive margin. However, given larger standard errors for prior prescription history estimates, we cannot conclusively determine whether or not previously unaware physicians have a larger response to detailing, the key prediction from the model of information.

The results are robust to other specifications and drugs. The findings are qualitatively similar in the extended sample, displayed in Appendix Table C2. We estimate the effect only on physicians receiving a detailing visit for the first time. The results are displayed in Appendix Table C3. We also conduct the same analysis on a set of doctors that have ever accepted a detailing visits related to any medical product during the sample period as a way to eliminate the never-takers. These results are in Appendix Table C4. Our key results are robust to both of these sample restrictions. We find qualitatively similar results, with a few exceptions in which physicians with prior experience respond negatively to the initial visit.

Experience and Beliefs

The model in Section 2.1 makes two clear predictions for the role of information among physicians that are aware of the drug's availability. First, the more experienced physicians (i.e. those who have prescribed higher volume of the drug in the past) should have less uncertainty about the drug quality and should therefore increase their prescriptions by less in response to additional information. Second, physicians that have higher mean prior beliefs about the drug quality match for their patients are less likely to have a large positive update in his belief about quality and should therefore increase their prescriptions by less in response to additional information. In fact, some physicians with very high priors may decrease their prescriptions in response to better information.

If information plays a role in physician response, the estimated interaction between detailing and either prior experience or prior beliefs should be negative. We find the opposite. Physicians with more prior experience prescribing the drug have greater responses to detailing visits, and physicians with high mean beliefs that prescribe more relative to their benchmark predicted share have higher positive response to detailing visits.

The findings are displayed in Table 4 and Figure 5. In Appendix Table C5 we present the results for the extended sample. The results are qualitatively similar, with the only exception being that for some drugs we do not observe a statistically significant interaction. The results are robust to defining the benchmark prescription rate using the prescription of "expert" physicians at AMCs in the same year rather than the last year of the sample and robust to more flexible belief interaction models (Appendix Table C6).

While it is possible that information provision is part of mechanism through which de-

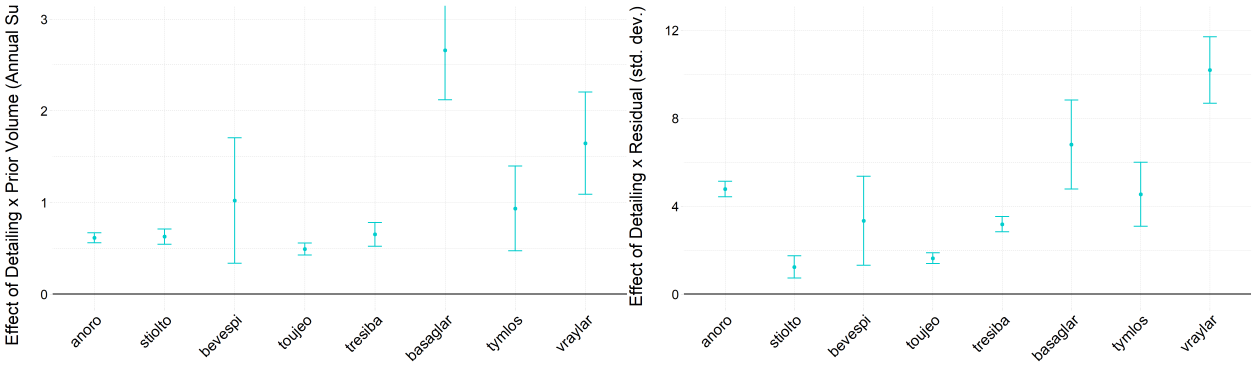
tailing encourages more prescriptions, our findings provide little support for the predictions from the model of learning. We do not find evidence that physicians with high uncertainty and lower mean beliefs about drug quality have greater responses to detailing visits. In fact, for all of the drugs in our empirical sample, we find the opposite pattern. We interpret these findings to be evidence against information as a key mechanism in the physician response to detailing. Rather, our results suggest that there are likely other kinds of advertising effects that drive physician responses.

Table 4: Differential Response by Prior Experience and Beliefs

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Prior Experience (Lagged 365-Day Supply)								
Detail	-2.032***	-2.311***	-1.027	0.148	-4.831***	-12.941***	-1.294	-1.235
	(0.557)	(0.658)	(2.578)	(0.667)	(1.646)	(2.498)	(0.836)	(5.962)
Interaction	0.613***	0.627***	1.021***	0.490***	0.652***	2.658***	0.934***	1.645***
	(0.028)	(0.043)	(0.349)	(0.033)	(0.066)	(0.275)	(0.236)	(0.285)
Panel B: Prior Beliefs (Lagged Benchmark Residual)								
Detail	0.811	-1.065	7.696**	-1.626	-0.456	-7.901**	0.530	-3.817
	(0.531)	(2.100)	(3.287)	(1.068)	(1.428)	(3.892)	(0.998)	(4.735)
Interaction	4.777***	1.233***	3.332***	1.633***	3.178***	6.796***	4.534***	10.186***
	(0.178)	(0.259)	(1.033)	(0.126)	(0.176)	(1.032)	(0.741)	(0.771)

Note: This table presents the 2SLS estimation results of intensive margin responses by experience and prior beliefs. All regressions are estimated on sample of doctors that have previously prescribed the drug. Each panel contains the intercept and slope term for the response to detailing interacted with either experience measured by lagged annual prescription supply (Panel A) or beliefs measured by the distance in standard deviation from the lagged benchmark residual (Panel B). Each estimation includes controls for year, specialty, patient-mix. Statistical significance based on clustered standard errors by physician with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 5: Differential Response by Prior Experience/Beliefs



(a) Lagged Experience

(b) Lagged Mean Beliefs

Note: This figure plots the intensive margin responses by experience and prior beliefs, corresponding to those in Table 4. Panel (a) displays the 2SLS estimates for the interaction between being detailed and the lagged annual supply of the drug. Panel (b) displays the 2SLS estimates for the interaction between being detailed and a standard deviation increase in the lagged benchmark residual. Both panels show the 95% confidence intervals around the point estimates.

4.2 Firm Selective Targeting

4.2.1 Empirical Specifications

In Section 2.2, we present a model in which profit maximizing firms will target their detailing efforts to physicians with high volume of patients and those with the highest expected response to detailing, conditional on patient volume. We argue that if firms believed information exchange was a dominant role in physician response to detailing, then the firms detail targeting policy should target the exact physicians that are predicted to respond to information. Specifically, the model predicts that if information was a driving mechanisms, then firms will target physicians that (i) are previously unaware of the drug (low ϕ), (ii) have less experience with/ high uncertainty about the drug (high σ_0), (iii) low prior beliefs about the drug (low μ_0), and (iv) have not been detailed in the past.

We turn to the data to test if firms are selectively targeting their detailing efforts to physicians that meet these criteria. For each drug in our empirical sample, we estimate the following linear probability model:

$$D_{idt} = \alpha_d^{exp}\text{Experience}_{id,t-1} + \alpha_d^{bel}\text{Belief}_{id,t-1} + \alpha_d^{det}D_{id,t-1} + + f_d(V_{idt}) + \Gamma_d X_{it} + \Lambda_{dt} + \nu_{idt} \tag{9}$$

With this, we assess whether a physician i is less likely to being detailed in year t if they had more experience prescribing the drug in the prior year ($\text{Experience}_{id,t-1}$), if they had high beliefs about drug quality (i.e., over-prescribing relative to his/her patient-mix-adjusted

benchmark level) in the prior year ($\text{Belief}_{id,t-1}$), and if they were detailed for that drug in the prior year ($D_{id(t-1)}$),

For our baseline specification, we use total prescriptions of target drug as our measure of physician experience, and we also estimate an alternative specification with an indicator for whether or not the physician had any positive prescriptions in the prior year. We control for the volume of patients with the relevant chronic illness seen by the physician, V_{idt}, which is an important factor in the potential total prescription response from a detailing visit. We use $f(V) = V + \sqrt{V}$ to match the concavity of detailing with respect to volume in the data. The vector X_{it} controls for patient population, patient-mix composition, indicators for physician main specialty, and county fixed effects. We estimate the model for each drug separately, and cluster standard errors at the physician level.

4.2.2 Results

The results for the key coefficients of interest (α_d^{exp}, α_d^{bel}, and α_d^{det}) are displayed in Table 5 and Figure 6. Note that while displayed in different figure panels, all coefficients relating to a particular drug come from the same regression.

We do not find evidence to support information-based predictions suggested by the model, and instead find strong evidence to the contrary. In Section 2.2, we argue that each of these coefficients should be negative if information is playing a dominant role in the mechanism through which detailing leads to more prescriptions. The coefficients we estimate are positive and significant in nearly every specification and for nearly every drug we include in the sample. These same results hold with few exceptions in the extended drug sample (Appendix Table C7). We also show the results are robust to sample restriction of doctors that have ever accepted a detailing visits related to any medical product during the sample period (Appendix Table C8).

Across all drugs, firms are more likely to detail physicians that have more prior experience with the drug, as measured by either total prescriptions or any positive prescriptions. For five out of eight drugs, firms are more likely to target high-belief physicians that over-prescribe the drug relative to their predicted benchmark. We find only one firm-drug pair that appears to target under-prescribers of the drug, Tymlos (for treating Osteoporosis). Firms are far more likely to detail physicians that have been detailed in the past. For most drugs in the sample, firms are more than 50 percentage points more likely to detail physicians they have already detailed than visit new physicians with similar volume, patient characteristics, and location.

Importantly, the firm targeting policies *are* consistent with the model presented in Section 2.2 and the evidence on physician responses in Section 4.1. Firms are targeting the physicians

that have the greatest responses to detailing, but these are not the physicians we expect respond to information.

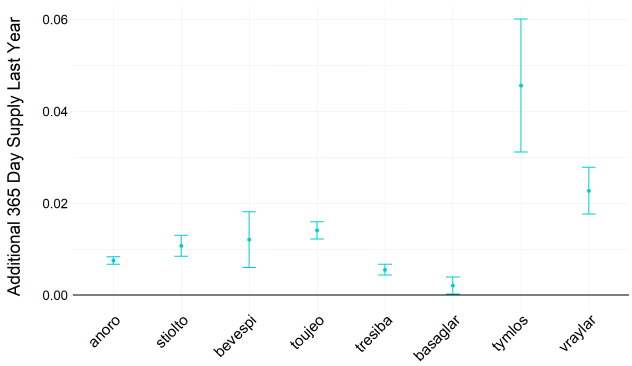
The targeting behavior of the firms cannot identify whether or not physicians learn from detailing visits. Instead, it provides evidence on which physicians the pharmaceutical firms believe will respond to detailing with more prescriptions. The targeting policies are not consistent with a model in which information provision is the primary mechanism driving the prescription response to detailing visits. As with the findings in Section 4.1, we believe these results suggest that the prescription response to detailing is due to other kinds of advertising effects rather than direct exchange of information, which we discuss more in Section 5.

Table 5: Firm Detailing Behavior

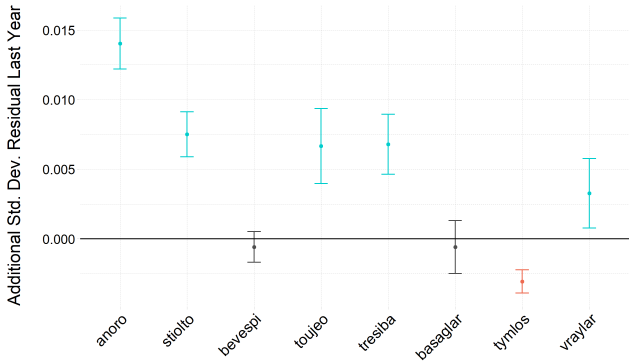
	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Experience = Prior Year Annual Prescription Supply								
Lag Experience	0.007***	0.011***	0.012***	0.014***	0.005***	0.002**	0.046***	0.023***
	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.007)	(0.003)
Lag Belief	0.014***	0.008***	-0.001	0.007***	0.007***	-0.001	-0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Lag Detail	0.578***	0.508***	0.280***	0.546***	0.634***	0.521***	0.464***	0.566***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.007)
Panel B: Experience = Any Prescription Prior Year								
Lag Experience	0.084***	0.081***	0.045***	0.081***	0.075***	0.017***	0.084***	0.110***
	(0.002)	(0.004)	(0.008)	(0.003)	(0.003)	(0.003)	(0.018)	(0.008)
Lag Belief	0.004***	0.003***	-0.001	0.007***	0.001	-0.002**	-0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Lag Detail	0.572***	0.505***	0.279***	0.541***	0.628***	0.521***	0.464***	0.561***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.007)

Note: Firms are more likely to detail more experienced, over-prescribing (higher mean beliefs), and previously detailed physicians. This table presents coefficients from a linear probability model of detail visits on an experience measure, belief measure, prior year detailing and other controls for year, patient-mix, and specialty. Each column represents results from a drug-specific regression. In Panel A, we use total prescriptions in the prior year as the measure of experience. In Panel B, we use any positive observed prescriptions in the prior year. Statistical significance is based on physician clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

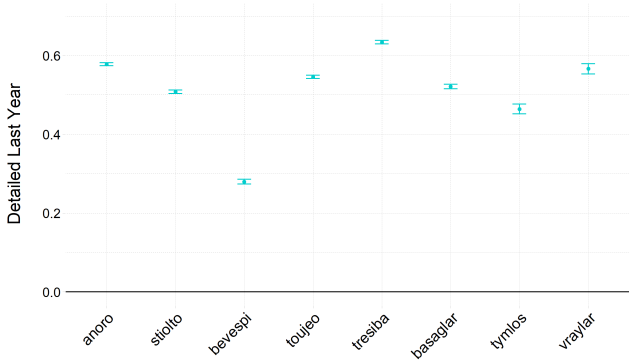
Figure 6: Firm Detailing Behavior



(a) Prior Year Experience



(b) Prior Year Mean Beliefs



(c) Prior Year Detailed

Note: These figures present the results of the firm target estimations shown in Table 5, column 1. The three panels represent three coefficients from a single estimation per-drug. Panel (a) displays the additional probably of detailing a physician with an additional annual supply prescribed in the prior year. Panel (b) displays the additional probability of detailing a physician relative to the physician's deviation from the benchmark prescription share in the prior year, measured in standard deviation. Panel (c) displays the additional probability of detailing a physician that was detailed in the prior year. The standard error bars denote 95% confidence intervals.

4.3 Detailing Over Time

A final prediction from our model is that there are diminishing information returns from detailing.[13] As physicians learn more about the drug from the firm, their peers, and trade

[13]This is the case when the underlying quality of the drug is not changing over time. For the drugs and time period in our sample, the manufacturing firms did not complete any efforts to collect data or

journals, the informative effect of detailing will fall over time. In this section, we use this observation to motivate two additional tests for information in physician responses and firm targeting.

First, we test for a declining effect of detailing over time. If awareness and experience with the drug plays an important role in physician responses, and physicians are becoming more aware and experienced over time, the effect of detailing will fall over time. We focus this analysis on extensive margin responses, which we view as the cleanest test of this hypothesis. We estimate the extensive margin response for all physicians using the cartesian product of the distance bins and indicators for years-after-entry as the instrument for endogenous variable of interest: detailing in each year.[14]

Extensive margin responses do not fall over time. In Table 6, we present the extensive margin results broken down by year after entry. In nearly every case, the extensive margin response of detailing increases with each year following entry. While it may be the case that physicians learn the most from detailing visits in the first year of entry, other effects of advertising seem to outweigh any diminishing role of information.

Table 6: Physician Extensive Margin Response to Detailing By Year

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Detail×	0.110***	0.136***	0.076***	0.144***	0.206***	0.231***	0.007	0.262***
Year 0	(0.011)	(0.010)	(0.007)	(0.009)	(0.010)	(0.014)	(0.025)	(0.045)
Detail×	0.157***	0.198***	0.261***	0.420***	0.344***	0.409***	0.052*	0.350***
Year 1	(0.014)	(0.017)	(0.036)	(0.016)	(0.014)	(0.042)	(0.028)	(0.051)
Detail×	0.236***	0.248***	0.654***	0.837***	0.636***	0.620***	0.034	0.549***
Year 2	(0.018)	(0.022)	(0.105)	(0.029)	(0.023)	(0.067)	(0.043)	(0.071)

Note: The effect of detailing on whether a physician writes any prescription for a drug is increasing over time. Each column represents an estimation for a particular drug where the treatment of interest, detailing, is interacted with the number of years after the drug's entry. Accordingly, the instrument is also interacted with year. The coefficients display the total effect, i.e. the final row displays the effect of detailing two years after drug entry. In the estimation, we allow for the effect to vary for every year of data, but we only display the first three. Each estimation includes controls for year, specialty, patient-mix. Statistical significance is based on physician clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, we test whether the detail targeting policies of firms are more focused on the less informed physicians in the initial years following entry. We estimate the same policy function as in Section 4.2 but allow the physicians prior experience, beliefs, and detailing history to interact with the year following entry. The results are presented in Table 7. Here, we use annual supply in the prior year as measure of physician experience. The analogous results

conduct post-entry clinical trials. Therefore, it is reasonable to assume that the information the firms can communicate is not changing very much over time.

[14]We can also estimate separate IV regressions for each year, and the results are quantitatively similar.

using an indicator for any prior experience are in Appendix Table C9.

Table 7: Firm Detailing Behavior By Year

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Lag Experience								
× Year 1	0.028***	0.070***	0.086***	0.031***	0.026***	0.022**	-0.059	0.044***
	(0.006)	(0.013)	(0.013)	(0.003)	(0.003)	(0.009)	(0.083)	(0.010)
× Year 2	0.007***	0.023***	0.010***	0.018***	0.013***	0.004***	0.069***	0.025***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.008)	(0.004)
× Year 3	0.011***	0.016***		0.018***	0.006***			0.020***
	(0.001)	(0.002)		(0.001)	(0.001)			(0.003)
Lag Belief								
× Year 1	-0.010***	0.009***	0.000	-0.002	0.001	-0.001	0.001**	0.004***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
× Year 2	0.011***	0.009***	0.000	0.012***	0.008***	-0.002	-0.005***	0.005***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)
× Year 3	0.022***	0.010***		0.009***	0.012***			-0.001
	(0.001)	(0.001)		(0.002)	(0.001)			(0.002)
Lag Detail								
× Year 1	0.611***	0.581***	0.288***	0.682***	0.689***	0.565***	0.635***	0.573***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.010)	(0.010)
× Year 2	0.656***	0.545***	0.254***	0.487***	0.655***	0.466***	0.405***	0.549***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.004)	(0.007)	(0.010)
× Year 3	0.593***	0.506***		0.497***	0.534***			0.576***
	(0.003)	(0.004)		(0.004)	(0.004)			(0.010)

Note: Firms do not prioritize information in the first year following the entry of the drug. Each column in the table represents an estimation for a particular drug. The estimations follow the same specification as Panel A of Table 5 but allows the three coefficients of interest (lag experience, lag beliefs, and lag detailing) to vary by year. The experience measure used is lag annual supply. The coefficients display the total effect, i.e. the final row displays the effect of having been detailed in the prior year 3 years following entry. Statistical significance is based on physician clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We do not find any clear evidence that firms are more concerned about information in the initial year following entry. For only one drug in our sample are firms less likely to target over-prescribing doctors in that first year. This is not the case for most drugs in the sample, and the results on prior experience and repeated detailing do not support a declining concern for information. Instead, it appears that the preference to target doctors with more experience and previous detailing visits is strongest in the first year.

In Table 8, we examine whether other physician characteristics are associated with these detail visit dynamics. Using NPI, we merge in the Medicare Provdider Catalog to obtain

information on physician gender, where they attended medical school, and year of graduation. We then append all physician-drug level data into one empirical sample and regress detail visit dynamics on doctor characteristics, specially looking at whether these characteristics are associated with ever being detailed, detailed at drug entry year, and number of repeat visits. In all specifications we control for patient-mix characteristics, market size, physician specialty, and drug fixed-effects.[15] Standard errors are clustered at the physician-drug level.

Table 8: Detailing Patterns and Physician Characteristics

	Ever Detail	Detail at Entry	Number of Repeat Visits
Male	0.072***	0.028***	0.186***
	(0.012)	(0.006)	(0.034)
Top 100 School	0.022***	0.002	-0.050***
	(0.006)	(0.004)	(0.011)
Grad 2000-10	0.035***	0.072***	-0.035
	(0.010)	(0.020)	(0.023)
Grad 1990-00	0.093***	0.102***	0.077**
	(0.018)	(0.021)	(0.024)
Grad 1980-90	0.130***	0.118***	0.093***
	(0.023)	(0.022)	(0.023)
Grad 1970-80	0.120***	0.125***	-0.047
	(0.021)	(0.022)	(0.028)
Grad 1960-70	0.083***	0.118***	-0.237***
	(0.020)	(0.022)	(0.057)
Grad 1950-60	0.015	0.175***	-0.245**
	(0.026)	(0.027)	(0.075)
Pat Char	Y	Y	Y
Drug FE	Y	Y	Y
N	966258	177059	177059

Note: This table presents coefficients from regression of Ever Detail, Detail at Entry, and Repeat Detail Visits on physician characteristics. Each regression includes controls for patient characteristics, market size, and speciality/expert indicators. We use data from only the 8 main drugs from our analytic samples and include drug fixed effects. The graduation year reference bin is after 2010. Standard errors are twoway clustered by NPI and drug. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.101$.

We find that male physicians are more likely to be detailed that female physicians, even after controlling for patient characteristics, physician specialty, and market size. Conditional on ever being detailed, they are also more likely to be detailed at drug entry year and receive more repeat visits.

We also find that physicians who graduated from a top 100 ranked medical school are

[15]See Appendix Table C10 for summary statistics of physician characteristics, by drug.

more likely to be detailed. However, conditional on being detailed once, they are less likely to receive follow up detail visits, perhaps suggesting that they learn quicker about drug quality from the first visit. Finally, we also look at differences by graduation year bins (with reference group being those that graduated after 2010). Compared to more recent medical school graduates, we find that older graduates are more likely to be detailed and more likely to be detailed at drug entry. The association with repeat visits is mixed with only the oldest graduates being less likely to experience repeat visits.

Taken together, the results of this section are consistent with those of Section 4.1 and Section 4.2. We do not find a diminishing response to detailing visits over time. We also do not find a pattern of firm detailing to suggest that they target doctors who would benefit most from learning (in any year). We do, however, find that other physician characteristics are associated with detailing and repeat detailing visits, perhaps suggesting that the direct advertising effect is dominating for these types of doctors.

The findings of this paper suggest that learning and information is not the primary mechanism through which physicians respond to detailing, and accordingly, it is not the principle motivation for which physicians' the firms decide to detail.

5 Discussion & Alternative Explanations

We have presented a set of facts which do not appear to support the role of information presented in Section 2. The estimates of firm targeting policies are consistent with the estimates of physician responses: firms target those with the greatest responses. However, we show that the physicians with the greatest responses are not the physicians that would benefit from learning/ information.

This naturally raises two questions. First, can our model explain the data without learning? And second, are there other models of learning and information that could better fit the data? In this section, we discuss these two questions in turn. We conclude that while models of information and learning can explain *some* of the data features we have presented above, it is a simple model of direct advertising effects (without information) that fits the data best.

5.1 Advertising without Information

The model presented in Section 2 can explain the data well without any learning. Consider a special case of our model in which physicians have some drug-specific preference given by δ_{ip}, and these preferences (beliefs) do not update in response to a detailing visit. Physicians

do not learn and respond to detailing visits only through the direct effect, θ_i.

$$u_{ip}(D) = \theta_i D + \delta_{ip}, \tag{10}$$

This model of advertising has a long history in motivating both the presence of advertising and the response to it through a shift in demand (Stigler and Becker, 1977; Becker and Murphy, 1993; Ackerberg, 2003). The exact mechanism of this direct effect of advertising is unclear. Ackerberg (2003) describes it as "prestige or image effects of advertising," distinct from objective descriptions of the product. This is a similar motivation to why Coca-cola and Pepsi advertise during the Superbowl, products that are widely known with relatively consistent characteristics. We interpret θ_i as being unrelated to any potential benefits to the patient, and therefore creating a wedge between consumer welfare and physician decision making.

Another possible mechanism specific to this context is the distribution of free samples. While we do not have any data on samples, research suggests that it is a common practice (King et al., 2020). Because samples do provide some price-benefit to patients, it raises the possibility that some of the direct effect of advertising is driven by patient demand. However, the drugs studied in this paper treat chronic illnesses, and free samples are unlikely to be a significant fraction of the total treatment cost (which is why they are offered to begin with). So we view this mechanism as another potential source for a wedge between physician decision making and the optimal allocation of drugs across patients.

The predictions made by this model closely match the patterns in the data. The physicians with the greatest response to detailing are those with the highest values of θ_i. As a result of their response to advertisement, these physicians will also end up prescribing the drug frequently and prescribing more than their peers. And, despite the fact that these physicians are becoming more experienced with the drug, the pharmaceutical firm will find it optimal to repeatedly return to the same set of physicians that have been identified as having high values of θ_i. Table 8 above may provide insight about who these "high θ" doctors may be in terms of gender, medical school ranking, and years since medical school graduation.

5.2 Other Models of Information and Learning

We specified the model in Section 2 to both make clean predictions of the role of information and remain close to workhorse models of learning in the advertising literature (Ackerberg, 2003; Narayanan and Manchanda, 2009). However, there are other potential models of learning that could make different predictions.

When agents are Bayesians, as in Section 2, additional information provides diminishing returns as agent beliefs approach the truth. An alternative model of information provision and learning could involve repeated detailing as a form of communicating importance through more costly signalling (Spence, 1973).

In this kind of costly signalling model, a physician may not respond much if they are detailed only once, a relatively low-cost action by the firm. But after repeated detailing visits across several years, the physician begins to believe the firm that the information they are offering is valuable to their practice in particular.

While this dynamic could explain some features of the data—prevalence of repeated visits and increasing effects over time—it is contradicted by results on the over-prescribing (high belief) physicians. In the costly-signalling model, the firm repeatedly targets physicians that are under-prescribing relative to full-information. But detailed physicians in the data already prescribe more than experienced peers, and firms are more likely to target the physicians that over-prescribe by more, even conditional on prior detailing visits and absolute levels of experience.

Another possibility is that physicians are heterogeneous in their learning rates. For example, Narayanan and Manchanda (2009) show some physicians learn much faster than others in response to detailing visits. However, while this could explain why a certain subset of physicians would be preferred to receive detailing visits, these physicians should have even faster diminishing returns from information. This does not fit with the repeated detailing visits and increasing effects with respect to experience and time.

6 Conclusion

Detailing is a common practice used by pharmaceutical firms to market directly to physicians. While previous research has shown that these visits are successful in leading to additional prescriptions, less is known about the overall welfare implications of this practice. One way in which detailing visits can be welfare improving is through information exchange; drug representatives provide information about the drug (quality and existence) during these detailing visits and physicians then use this information to make better prescription choices for their patients. In this paper, we provide a model to explicitly specify this information exchange mechanism. We then use data from eight prominent drug entrants between 2014 and 2017 to test the model predictions.

Consistent with other findings in the literature, we find that detailing visits lead to greater prescription rates for nearly every drug in the sample. While we find some evidence that detailing visits increase awareness of the drug, we also show that response to detailing

is greater among physicians with higher prior experience and those whose prior beliefs are further from a true quality benchmark. These results suggest that while learning may play some role in the physician response, it is likely not a driving mechanism.

The model also predicts that if information plays a dominant role in physician response to detailing, then profit-maximizing firms will target physicians who benefit from information exchange. In other words, firms should be less likely to detail physicians that have received detailing visits before (already informed), have prescribed the drug in large volumes (already experienced), or are over-prescribing relative to their predicted benchmark (already have high mean beliefs about drug quality). The data reject all three of these claims. The targeting policies suggest that firms are interested in detailing physicians that show a willingness to prescribe the drug and they detail these physicians repeatedly. This is not consistent with a model in which information plays an important role in physician responses. Rather, it suggests that firms target physicians with traditional marketing materials in order to encourage already experienced physicians to increase their prescription rates.

Our model framework provides an important perspective on pharmaceutical detailing patterns by highlighting the role (or lack thereof) of information exchange and learning. The empirical results provide evidence that physician learning from information exchange is not a driving mechanism of pharmaceutical detailing, suggesting that detailing practices are primarily about traditional marketing incentives—brand reputation or prestige. While we suspect that these incentives and their prescription response may not be in the best interest of the patient, additional analyses that directly investigates the effect of detailing visits on patient outcomes is an important area for future research.

References

Ackerberg, D. A. (2001). Empirically Distinguishing Informative and Prestige Effects of Advertising. *The RAND Journal of Economics*, 32(2):316.

Ackerberg, D. A. (2003). Advertising , Learning , and Consumer Choice in Experience Good Markets : An Empirical Examination. *International Economic Review*, 44(3):1040.

Agha, L. and Zeltzer, D. (2022). Drug diffusion through peer networks: The influence of industry payments. *American Economic Journal: Economic Policy*, 14(2):1–33.

Alpert, A., Lakdawalla, D., and Sood, N. (2023). Prescription drug advertising and drug utilization: The role of medicare part d. *Journal of Public Economics*, 221:104860.

Anand, B. N. and Shachar, R. (2011). Advertising, the matchmaker. *The RAND Journal of Economics*, 42(2):205–245.

Becker, G. S. and Murphy, K. M. (1993). A Simple Theory of Advertising as a Good or Bad*. *The Quarterly Journal of Economics*, 108(4):941–964.

Carey, C., Lieber, E. M., and Miller, S. (2021). Drug firms' payments and physicians' prescribing behavior in Medicare Part D. *Journal of Public Economics*, 197.

Ching, A. T. and Ishihara, M. (2012). Measuring the informative and persuasive roles of detailing on prescribing decisions. *Management Science*, 58(7):1374–1387.

Coscelli, A. and Shum, M. (2004). An empirical model of learning and patient spillovers in new drug entry. *Journal of Econometrics*, 122(2):213–246.

Crawford, G. S. and Shum, M. (2005). Uncertainty and learning in pharmaceutical demand. *Econometrica*, 73(4):1137–1173.

Grennan, M., Myers, K., Swanson, A. T., and Chatterji, A. (2022). No Free Lunch? Welfare Analysis of Firms Selling Through Expert Intermediaries. *National Bureau of Economic Research*, page WP 24864.

Guo, T., Sriram, S., and Manchanda, P. (2020). "let the sunshine in": The impact of industry payment disclosure on physician prescription behavior. *Marketing Science*, 39(3):516–539.

Hincapie, A., Schlosser, E., Damachi, U., Neff, E., Llambi, L., Groves, K., and MacKinnon, N. J. (2021). Perceptions of the provision of drug information, pharmaceutical detailing and engagement with non-personal promotion at a large physicians network: a mixed-methods study. *BMJ open*, 11(1).

Huang, G., Shum, M., and Tan, W. (2019). Is pharmaceutical detailing informative? Evidence from contraindicated drug prescriptions. *Quantitative Marketing and Economics*, 17(2):135–160.

King, A. C., Schwartz, L. M., and Woloshin, S. (2020). A National Survey of the Frequency of Drug Company Detailing Visits and Free Sample Closets in Practices Delivering Primary Care. *JAMA Internal Medicine*, 180(4):592–595.

Larkin, I., Ang, D., Steinhart, J., Chao, M., Patterson, M., Sah, S., Wu, T., Schoenbaum, M., Hutchins, D., Brennan, T., et al. (2017). Association between academic medical center pharmaceutical detailing policies and physician prescribing. *Jama*, 317(17):1785–1795.

Manchanda, P. and Chintagunta, P. K. (2004). Responsiveness of physician prescription behavior to salesforce effort: An individual level analysis. *Marketing Letters*, 15(2):129–145.

Narayanan, S. and Manchanda, P. (2009). Heterogeneous learning and the targeting of marketing communication for new products. *Marketing Science*, 28(3):424–441.

Schnell, M. and Currie, J. (2018). Addressing the opioid epidemic: is there a role for physician education? *American journal of health economics*, 4(3):383–410.

Shapiro, B. T. (2018). Informational shocks, off-label prescribing, and the effects of physician detailing. *Management Science*, 64(12):5925–5945.

Shapiro, B. T. (2022). Promoting wellness or waste? evidence from antidepressant advertising. *American Economic Journal: Microeconomics*, 14(2):439–77.

Sinkinson, M. and Starc, A. (2018). Ask Your Doctor? Direct-to-Consumer Advertising of Pharmaceuticals. *The Review of Economic Studies*, 86(2):836–881.

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics*, 87(3):355–374.

Stigler, G. J. and Becker, G. S. (1977). De gustibus non est disputandum. *The American Economic Review*, 67(2):76–90.

Appendices

Appendix A: Physician Utility and Learning

In this appendix, we detail the physician prescription decision-making and learning process. We assume a risk-averse physician, i, learns about the quality of drug k, and makes prescribing decisions for her patients that maximize utility in each period, t.

In traditional drug learning models (e.g., Crawford and Shum, 2005; Coscelli and Shum, 2004), a physician will learn about drug-patient match values, which can be identified by following prescription decisions for a given patient over time. However, because our analytical sample is at the doctor-year level, our model aggregates the within-patient prescribing process in a way similar to that in Narayanan and Manchanda (2009). In our model, the physician learns about the average drug quality for their given patient mix, which can be thought of as the average drug-patient match value across all patients seen in that period.

Mathematically, there is some unknown value, Q_{ik}, which represents the true average quality of drug, k, when given to patients of physician, i. This varies by physician given differences in patient characteristics across physicians. As before, this can be thought of as the average patient-drug specific match value that is common in prescription learning models: $Q_{ik} = \frac{1}{P_N} \sum_{p=1}^{P_N} q_{pk}$ where p represents a single patient of physician i, with P_N total patients.

Let u_{ikt} be utility that physician i receives when prescribing drug k to their patient-set at time t. We follow the literature and define period-utility as follows:

$$u_{ikt} = \theta D_{ikt} + Q_{ik} + \varepsilon_{ikt}$$

Here, D_{ikt} indicates whether doctor i received a detailing visit for drug k at time t. Q_{ik} is the true (unknown) aggregate quality of drug k for patient's of physician i, and ε_{ikt} is a type I extreme value error term.[16]

The physician does not know the true drug quality measure, but forms beliefs about its value over time. At time t, physician i believes the true quality of drug k for her patients comes from a normal distribution with mean μ_{ikt} and variance σ^2_{ikt}. Mathematically, $Q_{ikt} \sim N(\mu_{ikt}, \sigma^2_{ikt})$. Both the mean belief and uncertainty are stochastic from the view of the physician who learns about quality over time and updates beliefs via Bayesian updating, described further below. With CARA utility and risk aversion parameter ϕ, we have the

[16] Again, we can think of this as a decision for each patient, in which the error term will include patient-specific match value deviations from the true mean quality measure Q_{ik}. Without loss, we can assume that the average deviation across all patients is 0 in expectation.

certainty equivalent utility function as follows:

$$u_{ikt} = \theta D_{ikt} + \mu_{ikt} - \phi\frac{\sigma^2_{ikt}}{2} + \varepsilon_{ikt}$$

Learning about True Drug Quality: Q_{ik}

In period $t = 0$, physician i starts with some prior belief about the quality of drug k, with mean μ_{ik0} and variance σ^2_{ik0}. In each period, the physician receives noisy signals of the true drug quality. She will likely receive these signals from many sources (e.g., patient feedback, peers, ...), but given the focus of this paper, we only include learning from detailing visits and assume all other learning is exogenous and captured iid in the error term.

If physician i is detailed, she receives noisy signal $\tilde{D}_{ikt} \sim N(Q_{ik}, \sigma^2_D)$. In other words, detailing visits can provide information about the quality of drug k for patients of physician i. While detailing information must be accurate of true drug quality Q_{ik} on average, they can also be noisy, which is denoted by signal variance σ^2_D. With normally distributed prior beliefs and detailing signals, a Bayesian updating physician will have the following posterior belief if detailed in time t: $Q_{ik} \sim N(\mu_{ikt}, \sigma^2_{ikt})$ where $\mu_{ikt} = \frac{\sigma^2_D}{\sigma^2_D+\sigma^2_{ik(t-1)}}\mu_{ik(t-1)} + \frac{\sigma^2_{ik(t-1)}}{\sigma^2_D+\sigma^2_{ik(t-1)}}\tilde{D}_{ikt}$ and $\sigma^2_{ikt} = (\frac{1}{\sigma^2_{ik(t-1)}} + \frac{1}{\sigma^2_D})^{-1}$.

Now, re-arranging terms to put in the format of the in-text equation in section 2.1, we have

$$u_{ikt} = \theta D_{ikt} + \mu(D_{ikt}) - \phi\sigma(D_{ikt})^2 \tag{A.0}$$

where $D_{ikt} \in \{0, 1\}$ indicates detailing visit to physician i for drug k in time t, and

$$\mu(D_{ikt}) = \begin{cases} \mu_{ik(t-1)} + \frac{\sigma^2_{ik(t-1)}}{\sigma^2_D+\sigma^2_{ik(t-1)}}\left(\tilde{D}_{ikt} - \mu_{ik(t-1)}\right), & \text{if } D_{ikt} = 1 \\ \mu_{ik(t-1)}, & \text{otherwise} \end{cases} \tag{A.1}$$

$$\sigma(D_{ikt})^2 = \begin{cases} \left(\frac{1}{\sigma^2_{ik(t-1)}} + \frac{1}{\sigma^2_D}\right)^{-1}, & \text{if } D_{ikt} = 1 \\ \left(\frac{1}{\sigma^2_{ik(t-1)}}\right)^{-1}, & \text{otherwise} \end{cases} \tag{A.2}$$

Writing utility in this format allows us to highlight the role of information in physician response to detailing. As we discuss in Section 2.1, there are both direct and indirect effects of detailing on physician utility. The direct effect comes from the first term in equation A.0, through θ. This captures "brand" effects of advertising, such as perceptions of prestige or brand loyalty.

The second term (equation A.1) captures the effect of a detailing visit on the physician's

average belief of drug quality. Recall that $\tilde{D}_{ikt}$ is an unbiased signal of true drug quality Q_{ik} and that $\mu_{ik(t-1)}$ captures the physician pre-detailing belief about drug quality. Therefore, in expectation, the physician's utility response will be greatest when $\left(Q_{ik} - \mu_{ik(t-1)}\right)$ is very large, i.e. the physician has mean prior beliefs below the true drug quality (pessimistic priors).

Finally, the third term (equation A.2) captures the effect of a detailing visit on the physician's uncertainty about drug quality. Importantly, this effect is positive and increasing in D_{ikt} regardless of whether the physician's priors over- or under-estimate drug quality.

Appendix B: Expert Benchmark Analysis

In this appendix, we detail the two-step benchmark analysis used to back out a measure of physician prior beliefs about drug quality.

We first select a subset of exogenously un-detailed expert physicians to determine the "true" drug quality match as a function of patient-mix controls: $\widehat{Q}_{it}(X_{it})$. Specifically, we use the 2019 prescription shares and patient composition data for physicians in Academic Medical Centers with high conflict-of-interest scores to estimate the following benchmark model (separately for each target drug in our empirical sample):

$$\left(\frac{\text{Prescribed Beneficiaries}_{it}}{\text{Total CC Beneficiaries}_{it}}\right) = \Phi(X_{it}'\kappa) \tag{B.1}$$

Here, the left-hand-side variable is the share of Medicare Beneficiaries with the associated chronic condition that is treated with the target drug. We use a probit specification given the share is bounded between 0 and 1. X_{it} is a vector of patient-mix controls and indicator for physician main specialty.

We then use the estimated benchmark model coefficients to predict what each non-expert physician prescription share *should* be, given their yearly patient-mix and specialty: $\widehat{Q}_{it}(X_{it}) = \Phi(X_{it}'\hat{\kappa})$. We interpret this $\widehat{Q}_{it}(X_{it})$ value as the true drug quality match for a given physician-year.

Finally, we calculate the physician-year prescription share residual to define mean beliefs such that $Belief_{it} = (RxShare_{it} - \widehat{Q}_{it}(X_{it}))$, a measure of how far off a physician is prescribing from their true drug-quality match value. If $Belief_{it} > 0$, a physician is prescribing *more* than they should given their patient-mix and therefore has overly optimistic beliefs about the quality of the drug. Conversely, a physician with $Belief_{it} < 0$ is under-prescribing and therefore has pessimistic beliefs about the quality of the drug.

Appendix C: Tables and Figures

Table C1: Extended Sample Drugs and Unobserved FDA Indications

Drug Name	Chronic Condition	Manufacturer	Entry Year	Indications Unobserved in Medicare Data
Namzaric	Alzheimer's Disease	Adamas Pharmaceuticals	2015	moderate to severe; stabilized on memantine and donepezil
Corlanor	Chronic Heart Failure	Amgen Inc.	2015	max beta-blockers; LVEF $< 35\%$; heart rate ≥ 70
Glyxambi	Diabetes (II)	Boehringer Ingelheim	2015	not type I; empagliflozin & linagliptin appropriate; no renal impairment
Xultophy	Diabetes (II)	Novo Nordisk	2016	not type I; not controlled on basal insulin or liraglatide
Soliqua	Diabetes (II)	Sanofi	2017	not type I; not controlled on basal insulin or lixisenatide
Repatha	Hyperlipidemia	Amgen Inc.	2015	adjunct to diet and statins for those with HeFH, CVD, or HoFH
Praluent	Hyperlipidemia	Regeneron and Sanofi	2015	adjunct to diet and statins for those with HeFH or CVD
Aristada	Schizophrenia	Alkermes Inc.	2015	not dementia-related psychosis; administered by healthcare professional

Note: These drugs meet the selection criteria described in Section 3.2, but have specific FDA indications that cannot be accounted for using the aggregated Medicare Part D prescriber-year data. FDA indications are pulled from the official drug label at approval year, obtained at Drugs@FDA.

Table C2: Physician Response to Detailing (Extended Sample)

	repatha	glyxambi	aristada	corlanor	soliqua	praluent	xultophy	namzaric
Panel A: Any Prescription								
AnyDetail|	0.036***	0.023***	0.093***	0.021***	0.062***	0.052***	0.029***	0.453***
no prior Rx	(0.005)	(0.003)	(0.019)	(0.004)	(0.005)	(0.009)	(0.004)	(0.015)
AnyDetail|	0.040	-0.254	0.128	-0.120	-0.083	-0.360**	0.760*	0.109
prior Rx	(0.106)	(0.158)	(0.274)	(0.236)	(0.232)	(0.149)	(0.414)	(0.205)
Panel B: Prescription Share								
AnyDetail|	-0.003	0.025***	0.137**	0.001	0.079***	-0.018	0.032***	0.920***
no prior Rx	(0.005)	(0.004)	(0.058)	(0.004)	(0.010)	(0.011)	(0.008)	(0.056)
AnyDetail|	-0.197	-0.413	0.271	-0.767	-0.279	-0.992***	3.567*	6.932***
prior Rx	(0.146)	(0.382)	(2.143)	(0.549)	(0.973)	(0.275)	(2.057)	(1.615)

Note: See Table 3.

Table C3: Physician Response to First Detailing Visit

	anoro	stiolto	bevespi	toujeo	tresiba	basaglar	tymlos	vraylar
Panel A: Any Prescription								
AnyDetail|	0.206***	0.099***	0.110***	0.401***	0.295***	0.333***	-0.010	0.292***
no prior Rx	(0.018)	(0.015)	(0.014)	(0.016)	(0.016)	(0.033)	(0.020)	(0.026)
AnyDetail|	-0.241	-0.592	-0.452	1.354*	1.518**	0.922	0.233	0.102
prior Rx	(0.362)	(0.930)	(0.945)	(0.724)	(0.682)	(0.694)	(0.237)	(0.797)
Panel B: Prescription Share								
AnyDetail|	0.603***	0.066	0.030	0.844***	0.900***	-0.083	-0.028	1.514***
no prior Rx	(0.106)	(0.066)	(0.086)	(0.054)	(0.066)	(0.144)	(0.059)	(0.196)
AnyDetail|	-37.612***	-40.548	-21.311	-2.045	6.967	-162.321	7.667	12.840
prior Rx	(13.307)	(29.634)	(16.716)	(5.658)	(8.172)	(383.015)	(9.188)	(56.344)

Note: We replicate the findings in Table 3 using only the first detailing visit that a physician receives. We remove physicians from the sample for the years following the initial detail. See Table 3 notes for more details.

Table C4: Response among Physicians Ever Detailed

	anoro	stiolto	bevespi	toujeo	tresiba	basaglar	tymlos	vraylar
Panel A: Any Prescription								
AnyDetail|	0.215***	0.141***	0.183***	0.392***	0.347***	0.312***	0.038**	0.215***
no prior Rx	(0.013)	(0.013)	(0.020)	(0.013)	(0.013)	(0.027)	(0.017)	(0.024)
AnyDetail|	0.059	-0.016	0.215	0.372***	0.209**	0.121	0.189	-0.437
prior Rx	(0.038)	(0.096)	(0.255)	(0.095)	(0.095)	(0.159)	(0.182)	(0.322)
Panel B: Prescription Share								
AnyDetail|	0.289***	0.093***	0.044	0.570***	0.575***	0.216**	0.056	0.546***
no prior Rx	(0.047)	(0.031)	(0.093)	(0.032)	(0.038)	(0.085)	(0.038)	(0.107)
AnyDetail|	1.504***	-0.173	1.238	2.779***	2.218**	0.789	0.502	-0.721
prior Rx	(0.416)	(0.505)	(1.153)	(0.533)	(0.980)	(1.006)	(0.877)	(3.867)

Note: We replicate the findings in Table 3 using only physicians that have ever received a detail visit for any type of medical product during the sample period. See Table 3 notes for more details.

Table C5: Differential Response by Prior Experience and Beliefs (Extended Sample)

	repatha	glyxambi	aristada	corlanor	soliqua	praluent	xultophy	namzaric
Panel A: Prior Experience (Lagged 365-Day Supply)								
Detail	-0.814***	-1.928***	-0.280	-1.103**	-1.958**	-0.964***	0.522	24.920***
	(0.198)	(0.519)	(1.411)	(0.492)	(0.964)	(0.292)	(1.904)	(8.176)
Interaction	0.236***	1.239***	0.558***	0.267***	0.680***	0.251***	0.826**	0.561
	(0.037)	(0.206)	(0.099)	(0.038)	(0.121)	(0.026)	(0.382)	(0.385)
Panel B: Prior Beliefs (Lagged Benchmark Residual)								
Detail	-0.463*	-0.129	3.002***	0.236	0.527	-0.010	3.433***	-14.414***
	(0.256)	(0.362)	(1.163)	(0.444)	(0.603)	(0.272)	(1.318)	(4.788)
Interaction	0.379***	0.042	0.354*	-0.414	0.549**	0.476***	0.554	14.849***
	(0.058)	(0.126)	(0.205)	(0.666)	(0.254)	(0.077)	(0.556)	(1.559)

Note: See Table 4.

Table C6: Differential Response by Beliefs: Alternative Specifications

	anoro	stiolto	bevespi	toujeo	tresiba	basaglar	tymlos	vraylar
Panel A: Annual Expert Model								
Belief Interaction	4.694*** (0.185)	2.346*** (0.460)	2.028*** (0.454)	1.984*** (0.148)	3.288*** (0.182)	6.802*** (1.068)	1.525*** (0.239)	4.055*** (0.434)
Panel B: Flexible Interaction Specification								
Interaction| $(Belief > 0)$	2.616*** (0.447)	0.572** (0.260)	15.116*** (4.685)	0.920*** (0.203)	1.485* (0.799)	3.521* (1.965)	5.985*** (0.908)	11.085*** (2.206)
Interaction| $(Belief < 0)$	11.712*** (1.349)	7.249*** (1.322)	-1.340 (1.936)	7.610*** (2.161)	6.270*** (1.281)	15.525*** (3.490)	0.350 (1.028)	6.949 (7.147)

Note: This table presents the 2SLS estimation results of intensive margin responses by measures of physician prior beliefs. All regressions are estimated on sample of doctors that have previously prescribed the drug. Panel A presents the coefficient on the interaction between detailing and distance from lagged benchmark residual where the benchmark is based on "experts" annual share rather than their share in 2019. See Appendix 6 for details. Panel B presents the coefficient on the interaction between Detailing and an indicator for whether the distance from lagged benchmark is positive or negative. Here, we use the original benchmark model based on "expert" shares in 2019. Each estimation includes controls for year, specialty, patient-mix. Statistical significance based on clustered standard errors by physician with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C7: Firm Detailing Behavior (Extended Sample)

	repatha	glyxambi	aristada	corlanor	soliqua	praluent	xultophy	namzaric
Panel A: Experience = Prior Year Annual Prescription Supply								
Lag Experience	0.028*** (0.003)	0.034*** (0.005)	0.016*** (0.003)	0.039*** (0.004)	0.080*** (0.007)	0.048*** (0.007)	-0.007 (0.009)	0.002*** (0.001)
Lag Belief	0.000 (0.001)	0.001*** (0.000)	0.004*** (0.001)	0.003*** (0.000)	0.001 (0.001)	-0.002*** (0.000)	0.003*** (0.001)	-0.001* (0.000)
Lag Detail	0.633*** (0.002)	0.498*** (0.002)	0.590*** (0.009)	0.568*** (0.003)	0.451*** (0.003)	0.429*** (0.003)	0.426*** (0.003)	0.306*** (0.003)
Panel B: Experience = Any Prescription Prior Year								
Lag Experience	0.085*** (0.006)	0.094*** (0.011)	0.100*** (0.013)	0.095*** (0.010)	0.237*** (0.017)	0.127*** (0.007)	-0.005 (0.026)	0.018*** (0.002)
Lag Belief	-0.001 (0.001)	0.001*** (0.000)	0.004*** (0.001)	0.003*** (0.000)	0.001 (0.001)	-0.002*** (0.000)	0.003*** (0.001)	-0.001** (0.000)
Lag Detail	0.633*** (0.002)	0.497*** (0.002)	0.587*** (0.009)	0.568*** (0.003)	0.451*** (0.003)	0.428*** (0.003)	0.426*** (0.003)	0.304*** (0.003)

Note: See Table 5.

Table C8: Firm Detailing Behavior - Ever Detailed Doctors

	anoro	stiolto	bevespi	toujeo	tresiba	basaglar	tymlos	vraylar
Panel A: Experience = Prior Year Annual Prescription Supply								
Lag Experience	0.008***	0.012***	0.014***	0.015***	0.006***	0.002	0.055***	0.028***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.008)	(0.004)
Lag Belief	0.023***	0.012***	0.000	0.011***	0.011***	0.001	-0.005***	0.009***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.003)
Lag Detail	0.528***	0.476***	0.263***	0.493***	0.576***	0.483***	0.443***	0.492***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.008)
Panel B: Experience = Any Prescription Prior Year								
Lag Experience	0.107***	0.099***	0.052***	0.094***	0.096***	0.016***	0.102***	0.148***
	(0.003)	(0.005)	(0.009)	(0.004)	(0.004)	(0.004)	(0.021)	(0.011)
Lag Belief	0.009***	0.006***	0.000	0.010***	0.002	-0.001	-0.005***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Lag Detail	0.521***	0.472***	0.262***	0.487***	0.568***	0.483***	0.444***	0.485***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)	(0.008)

Note: We replicate the findings in Table 5 using only physicians that have ever received a detail visit for any type of medical product during the sample period. See Table 5 notes for more details.

Table C9: Firm Detailing Behavior By Year

	anoro	stiolto	bevespi	toujeo	tresiba	basaglar	tymlos	vraylar
Lag Experience								
× Year 1	0.084***	0.165***	0.219***	0.103***	0.124***	0.042***	-0.051	0.149***
	(0.017)	(0.027)	(0.024)	(0.010)	(0.007)	(0.014)	(0.115)	(0.017)
× Year 2	0.073***	0.146***	0.028***	0.101***	0.103***	0.026***	0.145***	0.130***
	(0.007)	(0.008)	(0.008)	(0.006)	(0.005)	(0.003)	(0.019)	(0.013)
× Year 3	0.106***	0.124***		0.128***	0.083***			0.096***
	(0.005)	(0.007)		(0.005)	(0.004)			(0.011)
Lag Belief								
× Year 1	-0.019***	0.006***	0.000	-0.001	-0.003**	-0.002	0.001**	0.004**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
× Year 2	0.001	0.004***	0.000	0.011***	0.003**	-0.003***	-0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.002)
× Year 3	0.009***	0.004***		0.007***	0.007***			-0.001
	(0.001)	(0.001)		(0.001)	(0.001)			(0.002)
Lag Detail								
× Year 1	0.612***	0.581***	0.287***	0.681***	0.687***	0.565***	0.635***	0.572***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.010)	(0.010)
× Year 2	0.654***	0.540***	0.254***	0.479***	0.648***	0.464***	0.405***	0.542***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.004)	(0.007)	(0.010)
× Year 3	0.585***	0.499***		0.484***	0.522***			0.570***
	(0.003)	(0.004)		(0.004)	(0.004)			(0.010)

Note: We replicate the findings in Table 7 using an alternative definition of experience. Here, Lag Experience is an indicator variable for whether the physician prescribed the drug in the prior year. See Table 7 notes for more details.

Table C10: Summary Statistics of Physician Characteristics

	anoro	basaglar	bevespi	stiolto	toujeo	tresiba	tymlos	vraylar
% Male	60.1	51.7	53.2	59.7	56.0	53.7	56.1	50.7
% Top 100 School	26.2	22.7	22.8	26.1	25.0	23.8	25.1	21.3
Mean Graduation Year	1994	1998	1998	1995	1996	1997	1997	1999
% Main Specialty	5.5	2.4	4.8	4.8	2.5	2.5	5.3	13.0
% At COI$\geq$ 30 AMC	3.6	3.5	3.7	3.6	3.5	3.5	3.7	2.8
Mean Market Size	1178.8	1660.4	1113.4	1255.2	1740.8	1707.9	528.1	542.6

Note: This table presents the summary statistics for key physician characteristics, conditional on being observed in the Medicare Provider Catalog with non-missing information on gender, medical school, and graduation year. Each column corresponds to a different drug in our empirical sample, and rows correspond to statistics of physicians who are potential prescribers of the drug as defined in Section 3.2. $Top100School$ is an indicator for whether the physician attended a medical school whose ranking is in the top 100 composite rank from Schnell and Currie (2018) or from US News Medical School Research Rankings in 2023. $MainSpecialty$ is an indicator for whether the prescriber's specialty is the main one that treats the chronic condition of interest (e.g. pulmonologist for anoro). We also report the percent of physicians who practice at an Academic Medical Center with high conflict of interest score as well as the average market size (beneficiaries with relevant chronic condition) across physicians.