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Theory and Evidence

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

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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 document strong evidence to the contrary.

Keywords: pharmaceutical advertising, physician learning, firm targeting
JEL Classification: I1, D8, L1, M3

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1 Introduction

Pharmaceutical firms often promote drugs through "detailing," wherein drug representatives meet directly with physicians, typically over a meal. Existing economic literature has established the success of these detailing visits in increasing targeted doctors' prescriptions of the intended drug (Carey et al., 2021; Agha and Zeltzer, 2022; Grennan et al., 2024).[1] While proponents argue that this marketing practice provides valuable information (Hincapie et al., 2021), there is limited 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 combine a model of physician learning and decision-making under uncertainty with a model of profit-maximizing firms to make predictions about the role of information in detailing visits. We test the predictions of the model using data from eight large detailing campaigns and physician prescribing behavior in Medicare Part D. While we cannot definitively rule out that physicians learn from detailing visits, our empirical findings provide little support for learning as the primary response mechanism. Instead, we argue the data is most consistent with preference-based advertising.

In the model, detailing visits provide a signal about the quality of the drug, and physicians update beliefs and write prescriptions accordingly. The model implies four key predictions about the role of information. First, the effect of detailing will be more pronounced among physicians otherwise unaware of the drug's existence, i.e. did not consider it in their past prescription decision. Second, physicians with less experience (more uncertain beliefs) will have greater increases in their prescriptions after a detailing visit. Third, physicians who are more pessimistic about a drug (lower mean of beliefs) will have greater increases in their

[1] A related pharmaceutical promotion technique is direct-to-consumer advertising, which researchers have shown also leads to increased prescriptions (see, for example, Avery et al., 2007; Sinkinson and Starc, 2018; Shapiro, 2022; Alpert et al., 2023).

prescriptions. 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 to maximize a drug's total prescription volume. The optimal targeting strategy details the physicians with the greatest expected response in prescriptions. Thus, if learning is the mechanism through which detailing visits increase prescriptions, the physicians targeted by the firms will resemble 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 Services (CMS), with physician-year level panel data on Medicare Part D prescriptions and patient characteristics from 2013 to 2019. We focus on 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 use 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 physician characteristics, as motivated by existing literature (Larkin et al., 2017; Grennan et al., 2024).

First, we test whether the effect of detailing is greater among physicians that might be previously unaware of the drug. We find that physicians with no previous prescription history have significant responses on the extensive margin. However, physicians with a previous prescription history have greater responses to detailing in their prescription share than those without any previous prescriptions. While the extensive margin responses are consistent with the model of information via awareness, the difference in prescription share responses are not.

Next, we test whether physicians with more experience with the drug and/or higher (optimistic) beliefs about drug quality have lesser 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, more experienced physicians and over-prescribing (optimistic) physicians have greater responses to detailing. This directly contradicts the hypothesis generated by the model of learning and suggests that other kinds of advertising effects may be more important in driving physician responses to detailing.

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. Firms dramatically favor revisiting previously detailed physicians rather than distributing potentially new information to new doctors. For all drugs in the sample, firms are more likely to target physicians that have more experience with the drug. For four out of eight drugs, firms are more likely to detail over-prescribers, and only appear to target under-prescribers for two drugs in the empirical sample.

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 are more likely to be targeted by the firms. While some learning may occur, 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 physicians

identified as receptive to this kind of advertising. We briefly expand on these alternative models and argue that the empirical findings are most consistent with a simple model of preference-based advertising (Becker and Murphy, 1993; Ackerberg, 2003; DellaVigna and Gentzkow, 2010).

Related Literature

There is a large literature on pharmaceutical advertising, mostly focused on demand-side responses. Research studying the effects of direct-to-consumer advertising shows these ads to be effective in increasing the demand for a particular drug (e.g., Avery et al., 2007; 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 effect of pharmaceutical detailing on prescription demand has been explored in the economics, marketing, and management literatures. To identify causal responses, many studies use physician fixed effects to account for endogenous detailing (e.g., Mizik and Jacobson, 2004; Datta and Dave, 2017; Carey et al., 2021, 2025).[2] In general, these studies show that physicians significantly increase prescribing in response to detail visits, though few identify the mechanism behind this response. 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, in the con-

[2]Alternative identification strategies in this area include causal machine learning (Newham and Valente, 2024), border-discontinuity in payment public disclosure laws (Guo et al., 2020), or exposure to high conflict of interest scores at Academic Medical Centers (Larkin et al., 2017; Grennan et al., 2024), the latter of which motivates the approach we use in this paper.

text of statin medications, detailing visits reduce prescriptions for contraindicated patients in support of their "informative detailing hypotheses." 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. While these papers identify whether physicians learn about specific aspects of prescribing, our paper asks whether the mechanism of learning can broadly explain physician responses to detailing across a variety of large detailing campaigns for new drug entrants.

From a modeling perspective, we combine elements from various strands of literature including physician learning about unobserved drug quality (e.g., Crawford and Shum, 2005; Coscelli and Shum, 2004), persuasive vs informative effects of advertising (e.g., Ackerberg, 2001; Anand and Shachar, 2011), and decision-making under uncertainty more broadly. In particular, we build on the structural learning literature in marketing and economics that develop and estimate models in which it is assumed that physicians prescribe in response to learning from detail visits (Manchanda and Chintagunta, 2004; Narayanan et al., 2005; Narayanan and Manchanda, 2009; Ching, 2010; Ching and Ishihara, 2012; Chintagunta et al., 2012).

In contrast, we empirically test the predictions of how detailing effects should vary across physicians in a model of learning and information, rather than estimate the parameters of a model in which learning is assumed. We show that the patterns in the data are *not* consistent with these model predictions. For example, our findings suggest that physicians with pessimistic and/or uncertain beliefs about a drug tend to respond *less* to detailing visits, whereas the standard learning model would predict otherwise. While we cannot rule out that physicians may learn something about the drug from detailing visits, our findings suggest that it is not a key mechanism in the responses to these visits.

Further, our study also expands on the previous literature by including analysis of firm-side targeting. While existing research recognizes that physicians are endogenously detailed,

few papers study the firm detail targeting decisions as its own object of interest. Using geographic variation in latent demand for smoking cessation treatments, Lawler and Skira (2022) find empirical evidence in support of informative targeting, documenting how detailing efforts for Chantix, a smoking cessation drug, increase following FDA removal of the black-box warning, likely to disseminate the positive information shock to physicians. Grennan et al. (2024) 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). The authors show that, in the case of cardiovascular drugs, these targeted doctors are also those that would have otherwise been below-average prescribers of the drug. In a sample of new drugs across several disease indications, we find that firms are more likely to target experienced and over-prescribing physicians, inconsistent with a model in which physician response is driven by informative detailing.

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 to the empirical analysis summarized in Section 4. 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 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.[3]

Firms collect or purchase detailed information on physician prescription behavior and patient-mix demographics in order to organize and target their detailing campaigns (Fugh-Berman and Ahari, 2007). Representatives are typically given a local territory and ranking of physicians in the area according to their market size and past prescribing history in that class of drugs. They use the collected information about physicians to decide who to visit, and their compensation (via bonuses) is often tied to the prescription-based goals. Thus, the representatives have an incentive to visit the physicians where they believe they will have the greatest affect on total prescriptions.

The representatives concentrate on a single drug or small group of drugs that can be used independently or together in treating a given condition. They are prepared by the firms with specific information and content, and they are expected to deliver that content to all physicians that they visit. This can include a sales pitch, marketing literature, information pamphlets, etc. Importantly, according to the Pharmaceutical Research and Manufacturers of America (PhRMA) Code of Ethics, information exchanged during detailing meals must "be accurate and not misleading" and align with FDA requirements.[4] If physicians request additional information outside of the drug representatives purview, they are encouraged to

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

[4]See `https://www.phrma.org/resources/code-on-interactions-with-health-care-professionals`, accessed 4.18.2025.

use other avenues available to communicate directly with experts at the pharmaceutical company (potentially outside of the marketing department).

While pharmaceutical manufacturing firms have used this practice to market drugs to physicians since the mid-century, it has recently drawn more policy attention over conflict of interest concerns, such that detailing visits might be compromising objective decision making by physicians (Guo et al., 2020). For example, Academic Medical Centers (AMCs) implemented policies restricting or prohibiting such marketing interactions between physicians and pharmaceutical companies (Larkin et al., 2017). On a national level, the Physician Payments Sunshine Act (one component of the Affordable Care Act), improved transparency on the relationships between pharmaceutical firms and physicians via mandatory public reporting of detailing interactions, which is where the data for this project originates.

Before moving to the empirical section of this paper, we first introduce a stylized model of physicians and firms in which detailing impacts prescription behavior only through information and learning. In the model, physicians write prescriptions to maximize expected drug quality for a given patient. Detailing visits provide information about the existence and quality of the drug, allowing physicians to update their consideration set and beliefs about the drug for their patients. We pair this with a model of profit-maximizing drug manufacturing firms that decide which physicians to target for detailing visits. With this stylized model, we derive 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 prescribing the drug of focus to patient p. 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, $u_{ip}(\cdot)$ is the utility relative to the next best option. To model the role of detailing visits, we express this utility as a function of detailing $D_i \in \{0, 1\}$ such that $u_{ip}(D_i)$ is a sum of two components: the mean of beliefs about drug quality for a given patient, $\mu_{ip}(D_i)$, and variance of that belief, $\sigma^2_{ip}(D_i)$. For a particular physician, deciding whether to prescribe a particular drug to a particular patient, we write:

$$u_{ip}(D_i) = \mu_{ip}(D_i) - \psi\sigma^2_{ip}(D_i) \tag{1}$$

where $D_i \in \{0, 1\}$ is an indicator of whether the physician is detailed and ψ relates to the physician's risk aversion. The physician's beliefs, $\mu(D_i)$ and $\sigma(D_i)$, are functions of whether or not the physician is detailed, with $\mu_{ip}(1)$ and $\sigma^2_{ip}(1)$ representing posterior beliefs after potentially learning from a detailing visit, $D_i = 1$. In Appendix B, we show how this utility framework can be derived from a model of Bayesian physicians with constant absolute risk aversion.

When a physician receives a detailing visit, the utility from prescribing is influenced through the effect detailing has on the physician's beliefs about drug quality for a given patient, p. The first term captures the effect of a detailing visit on the physician's average belief of drug quality, and the second 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 that is 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. The consideration set can be affected by whether or not a physician is detailed: $\Omega_i(D_i) \in \{(O, d), (O)\}$. In particular, we will assume that for all doctors, a detail visit guarantees that the drug is in the consideration set: $\Omega_i(1) = (O, d)$.

Let S_i denote the share of the total number of potential patients, N_i, to which a physician

will prescribe the drug. This share is 0 for physicians who are unaware of the drug (i.e., those who do not have d in their consideration set), and equal to the share of patients with positive expected utility otherwise. Both the consideration set and expected utility can be influenced by the detailing visit, D_i, such that:

$$S_i(D_i) = \mathbb{1}(d \in \Omega_i(D_i)) \times \frac{1}{N_i} \int_p \mathbb{1}(u_{ip}(D_i) > 0) dp \tag{2}$$

Let ΔS_i describe the effect of a detailing visit on the share of patients prescribed the drug by a given physician so that $\Delta S_i = S_i(1) - S_i(0)$. Combining Equation (2) with the fact that a detail visits adds the drug to the consideration set with certainty, i.e., $\Omega_i(D_i = 1) = (0, d)$, yields the following:

$$\Delta S_i = \frac{1}{N_i} \int_p \left[\mathbb{1}(u_{ip}(1) > 0) - \mathbb{1}(d \in \Omega_i(0)) \mathbb{1}(u_{ip}(0) > 0) \right] dp \tag{3}$$

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. There are two channels through which information provided by detailing visits can affect prescriptions: awareness of and beliefs about drug quality.

Awareness

The awareness information channel occurs through spreading the word about the existence of the drug. For unaware physicians, the drug is not in the consideration set by definition, and thus they cannot prescribe the drug to their patients. Because a detailing visit guarantees that the physician is now aware of the drug (i.e., $d \in \Omega_i(1)$), the visit may lead the physician to begin prescribing the drug.

The model makes two predictions relevant to awareness. First, because detailing visits add a new drug to the consideration set for otherwise unaware physicians, we should see an effect of detailing on the extensive margin of prescribing the drug to any patient among

physicians who would otherwise be unaware of the drug. Second, the effect of detailing on prescription share should be smaller for physicians that are already aware of the drug.[5]

Beliefs about Drug Quality

This information channel comes from the information about drug quality that is potentially given to the physician during a detail visit. Physicians are uncertain about the quality of a drug in treating a given patient but have a normally distributed prior belief about this quality with mean μ_{0ip} and variance σ^2_{0ip}. If a physician is not detailed ($D_i = 0$), then they do not update their beliefs. If they are detailed ($D_i = 1$), then the information provided by the detailing representative is a noisy signal, $\tilde{D}_p$, about the underlying true quality of the drug for a patient, μ^*_p, such that $\tilde{D}_p \sim N(\mu^*_p, \sigma^2_D)$.[6] The physicians update their beliefs according to Bayes rule. Their posterior mean and variance of drug quality, conditional on detailing, is given by the following:[7]

$$\mu_{ip}(D_i) = \begin{cases} \mu_{0ip} + \frac{\sigma^2_{0ip}}{\sigma^2_D + \sigma^2_{0ip}} \left(\tilde{D}_p - \mu_{0ip} \right), & \text{if } D_i = 1 \\ \mu_{0ip}, & \text{if } D_i = 0 \end{cases} \tag{4}$$

$$\sigma^2_{ip}(D_i) = \begin{cases} \sigma^2_{0ip} \left(\frac{\sigma^2_D}{\sigma^2_{0ip} + \sigma^2_D} \right), & \text{if } D_i = 1 \\ \sigma^2_{0ip}, & \text{if } D_i = 0 \end{cases} \tag{5}$$

Recall that conditional on the drug being in the physicians information set, the effect of

[5]Note that this follows from Equation (3): $\frac{1}{N_i} \int_p [\mathbb{1}(u_{ip}(1) > 0) - \mathbb{1}(u_{ip}(0) > 0)] \, dp \leq \frac{1}{N_i} \int_p [\mathbb{1}(u_{ip}(1) > 0) - 0] \, dp$

[6]An implicit assumption is that the information content, i.e. signal variance, of detail visits are homogeneous. A possible alternative is that firms use more informative visits for less experienced physicians. This would reinforce the key predictions of the model.

[7]In Section 5, we discuss other models of learning in which physicians are not necessarily Bayesians in the manner specified here.

detailing, ΔS_i depends on $u_{ip}(1) - u_{ip}(0)$ (see Equation (3)). Therefore, we can compare the above updated beliefs in Equations (4) and (5) relative to prior beliefs (μ_{0ip} and σ^2_{0ip}) to guide predictions about the effect of detailing on physician utility via their Bayesian learning. See Appendix B for additional details and derivations.

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^2_{0ip}. The detailing effect should be larger for physicians with higher prior uncertainty about the drug's quality for their patient set (high σ^2_{0ip}). Second, the effect of detailing is decreasing in the prior mean, μ_{i0p}. Physicians who are more pessimistic about a drug (relatively low μ_{0ip}) will have greater positive response to detailing visits compared to physicians with more optimistic prior mean beliefs (relatively high μ_{0ip}). 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:

(i) Unaware physicians will have a weakly positive response to detailing on the extensive margin. And, aware physicians will respond less to detailing visits relative to those who are otherwise unaware.

(ii) Physicians with less uncertain beliefs will respond less to detailing visits relative to those with more uncertain beliefs.

(iii) Physicians with higher mean beliefs (more optimistic about drug quality) will respond less to detailing visits relative to those with lower mean beliefs about drug quality.

(iv) Repeated detail visits to the same physician will have diminishing returns from information.

2.2 The Firms

We 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, $D_i = 1$, for their particular drug. Each filled prescription generates profit π,[8] and the cost of detailing is given by some convex function $C()$. The firm observes the set of potential prescribers and information about their patients, e.g. the number of patients that might benefit from the drug. The profit of the firm is then the sum across physicians of per-prescription profit π multiplied by the number of prescriptions written by a physician $N_i \times S_i(D_i)$, less detailing costs:

$$\Pi = \sum_i \pi N_i S_i(D_i) - C(\sum_i D_i). \tag{6}$$

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, $C(\sum_i D_i) = c \sum_i D_i$, the firm will detail all physicians that satisfy

$$\underbrace{\pi N_i \Delta S_i}_{\text{Additional Profit from Detail Visit}} > c \tag{7}$$

In other words, conditional on their total number of potential patients, N_i, firms will target their detailing visits to physicians that have greater expected responses in their pre-

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

scription behavior, i.e. those with larger ΔS_i.

Firms have potentially more complex detailing costs. But for many kinds of cost functions, the physicians that firms decide to detail 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 heterogeneous across physicians, perhaps due to local traveling or transportation costs. In this case, predictions that we derive from the model will apply across physicians *within* the same geographic area.[9]

Role of Information

Because firms want to target physicians with high expected response to detailing, the predictions about the role of information in the model of the firm are analogous to those in 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. Conditional on patient volume and characteristics, our model of informative detailing predicts that firms will target their detailing visits to physicians that:

(i) are unaware of the drug (those with $d \notin \Omega_i(\cdot)$)

(ii) have more uncertainty about the drug quality (those with relatively high σ^2_{0ip})

(iii) have low prior beliefs about the mean quality of the drug for their patients (those with relatively low μ_{0ip})

(iv) have not been detailed in the past.

[9]In our empirical exercise, we include area controls at different levels (e.g. county, zip code) to account for this possibility.

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) conflict-of-interest 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 The Center for Medicare and Medicaid Services (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 refer to these interactions as detailing visits. The inter-quartile range of the value of all meals in the data is \$11 to \$19.

Using this data source, we construct a physician-year panel with information on number of detailing visits in total and by drug from January 2015 to December 2019. We define D_{idt} as an indicator for whether physician i received a detailing visit for drug d at some point during year t. We define detailing visits at the yearly level as this is the finest level in which we observe the physician-drug prescription data described below. We note, however, that a majority (80%) of physicians in our sample that are detailed in a given year are done so in the first two quarters of the year, thus limiting potential measurement error that may occur due to timing of detail visits and prescription shares. Further, a majority (70%) of detailed physicians in our empirical sample receive a visit that uniquely discusses the focal drug.

When multiple drugs are discussed, the other drugs are typically relevant to the specific chronic illness targeted by the focal drug.

Medicare Part D

The CMS 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 combine these data with the Medicare Provider Catalog to obtain information on physician characteristics such as gender, where they attended medical school, and year of graduation.[10] For each drug, d, we compute a physician-year specific prescription share ($RxShare_{idt}$) defined as the total number of annual prescription (365-day supply) claims attributed to the physician divided by the number of patients seen by the physician with the relevant chronic condition in a given year.

We match the prescription data to the OpenPayments data using a physician-level mapping to NPI provided by CMS. The data do not have complete coverage of the earlier years in the data. To fill the gaps, we sequentially match physicians in the unmatched OpenPayments data to the NPI data on physician name only, name and state, name and city, and finally name and zipcode. In each step, we keep only physicians that are uniquely identified in both the OpenPayments data and the universe of physicians with registered NPI numbers. We

[10]See Appendix Table A1 for summary statistics of physician characteristics, by drug.

are able to identify the NPI for 98.2% of physicians in the OpenPayments data and 99.8% of the total number of payments. Through this merge, we obtain a physician-year panel with both detailing visits and prescription claims by drug, in addition to patient-mix and physician characteristics.

AMSA Scorecards

The American Medical Student Association (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 follow Grennan et al. (2024) in creating a summary measure for each AMC-year by summing the score across all the fields of the scorecard. We then take the yearly center average for the two years in which we have access to AMSA scorecards (2014 and 2016). Finally, we define an AMC as having a strong conflict of interest policy if their total score is greater than 30, the median summary score across centers.

3.2 Sample Selection

We study detailing campaigns of branded drugs that enter the market between 2015 and 2017. We define market entry as the first year in which the drug has both non-zero prescription rates and detailing visits. We consider all new drugs in this period that have 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: six diabetes medications, three medications for chronic obstructive pulmonary disease (COPD), three medications for hyperlipidemia and chronic heart failure, two medications for mental health conditions such as schizophrenia and bipolar disorder, one Alzheimer's disease medication, and one medication for osteoporosis.

Next, we remove 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 eight remaining drugs in the sample are presented in Table 1 along with the chronic condition they treat, the drug manufacturer, and the entry year.

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 eight more specialized drugs as well. We refer to these drugs as the *extended sample*. In Appendix Table A2, 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.

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.[11] 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.

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

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 three 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 two years after entry, only a small fraction of total detail visits are allocated to physicians that have never been detailed for the drug, despite detailing only a small fraction of doctors overall (Table 2).

And finally, we show that the conflict of interest scores at Academic Medical Centers 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.

Importantly, we note that there are likely 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 between a physicians practice location and the closest Academic Medical Center with a high conflict of interest score. 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 restrictions 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 stylized model of information and learning in Section 2. We estimate both the physician prescription response to detailing visits and firm detail targeting policies. Following the predictions in Section 2, we test for differences in the relationship between physician response and/or firm targeting by levels of awareness, prior uncertainty, and prior mean beliefs. In this section, we first define empirical measures of the various information channels of interest. We then present the empirical specifications and estimation results for the physician response predictions, followed by the empirical specification and results for the predictions of the firm.

4.1 Measures of Awareness, Uncertainty, and Mean Beliefs

Recall from Section 2.1 that awareness of a drug d is defined by a physicians' consideration set. A physician is aware of the drug if d is in their consideration set and unaware if not. While physician awareness is unobservable, we know that a physician must be aware of the drug if they prescribed the drug in the past.[12] In our empirical test for physician

[12]We can only observe whether a physician has previous prescriptions in the Medicare Part D data. This does not affect the conclusion that these physicians are certainly aware but affects the degree to which the

prediction (i), we ask whether there is an extensive margin response among those without a history of prescribing the drug, and whether those with a previous prescription history respond relatively less to detailing visits. We note that the extent to which those who did not prescribe the drug in the past are still aware of the drug will reduce both the theoretical importance of this channel and the model-predicted magnitude of the estimates but not the predicted sign.

Next, we define physician prior uncertainty (σ^2_{0ip} from section 2.1) as inversely related to the physician's previous experience under the assumption that physicians with more experience prescribing the drug have less uncertainty about the drugs' quality, all else equal. We measure physician experience using the lagged prescription volume measured in 365-day supply. Physicians with more experience prescribing the drug, i.e. those with higher prescriptions of the drug in the last year, are less uncertain about the quality of the drug for their patient. Conversely, physicians who prescribed the drug to relatively fewer patients, conditional on same patient mix, are more uncertain. In our empirical test for physician prediction (ii), we ask whether physicians with higher prescription volume in the prior year respond relatively less to detailing visits.

Finally, we use an expert benchmark model approach to estimate a measure of physician mean prior beliefs about drug quality. Recall from Section 2.1 that mean beliefs, μ_{ip}, represent the expected mean quality of the drug in treating a patient, with some unknown *true* quality given by μ^*_p. Our goal with the benchmark model is to measure where physicians mean beliefs fall relative to the true drug quality and then use this measure to test whether physicians with relatively higher mean beliefs about the drug quality respond less to detailing visits.

The expert benchmark model proceeds in three steps. In the first step, we use a subset of "expert" physicians to estimate a mapping between patient characteristics and prescription

non-prescribing physicians might still be aware of the drug.

share. We define "expert" physicians as those who work at an academic medical center with high conflict of interest score, have ever prescribed the drug, and focus on the shares in the last year of the sample, $t = 2019$.[13] Assuming these "expert" physicians prescribe with full information, we can use their observed prescription share as a measure of true drug quality, μ_p^*, for a given patient-mix, p. We estimate a Probit model using data from these expert physicians, where X_{it}' is a vector of patient characteristics and physician specialty.

$$RxShare_{idt} = \Phi(X_{it}'\kappa) \tag{8}$$

In the second step, we apply this benchmark model to *all* physicians in the sample to determine what a physicians' prescription share *should* be if they had behaved similar to the experts: $\widehat{RxShare}_{idt} = \Phi(X_{it}'\hat{\kappa})$.

In the third and final step, we measure physician prior beliefs using the lagged benchmark share residual. Specifically, we use the difference between lagged observed prescription share $RxShare_{id(t-1)}$ and benchmark predicted prescription share $\widehat{RxShare}_{id(t-1)}$. This measures how far a physician is prescribing from their "true" drug quality level. If the residual is positive, a physician is prescribing *more* than the average expert given their patient-mix and therefore may have more optimistic beliefs about the quality of the drug. Conversely, if the residual is negative, the physician is under-prescribing and therefore may have more pessimistic beliefs about the quality of the drug. In our empirical test for physician prediction (iii), we ask whether physicians with higher mean beliefs about drug quality (higher benchmark model residual in the prior year) respond relatively less to detailing visits.

[13] In addition to using the last sample year, we have also estimated a benchmark model for each sample year. We discuss these results in Section 4.4.

4.2 Physician Response to Detailing

4.2.1 Empirical Specifications

The goal of our analysis of physician behavior is to compare the predictions from the model in Section 2 to empirical patterns of the effect of detailing visits on prescriptions.

Following the first part of physician prediction (i), we estimate Equation (9) for the set of doctors that have not prescribed the drug d up to time $t-1$ (potentially unaware).

$$\mathbb{1}(RxShare_{idt} > 0) = \beta_d D_{idt} + X'_{it}\gamma_d + \lambda_{dt} + \epsilon_{idt} \tag{9}$$

The second part of prediction (i) as well as (ii)-(iii) refer to the relative differences in the response to detailing across physicians with different information states. To test these predictions, we use Equation (10) with $InfoChannel_{id,t-1}$ corresponding to whether the drug was prescribed in the past (measure of awareness), lagged prescription volume (measure of prior uncertainty), and the lagged residual from the expert benchmark model (measure of mean prior beliefs). Because the measures of prior uncertainty and mean prior beliefs are only defined for physicians with some previous prescriptions, we estimate the later two models using only physicians that have a previous history of prescribing the drug.

$$RxShare_{idt} = \left(\beta_d + \beta_d^{info} InfoChannel_{id,t-1}\right) D_{idt} + X'_{it}\gamma_d + \lambda_{dt} + \epsilon_{idt} \tag{10}$$

In both equation, $D_{idt} \in \{0, 1\}$ indicates whether physician i received any detailing visit for the target drug in year t. We scale $RxShare_{idt}$ to be measured in percentage points, i.e. between 0 and 100.

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 to be correlated with things about the physician's prescriptions that we cannot observe, ϵ_{idt}. To identify the causal effect of detailing, we use the distance between the physician's practice zip code and

the nearest AMC with a high conflict of interest score as a plausibly exogenous shift of the detail visit propensity (Grennan et al. (2024)).[14] We show that the conflict of interest policies of the nearest AMC reduce detailing propensity, and this reduction spills over to nearby physicians due to geographic economies of scale in marketing (see Figure 3). 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 discipline the appropriate bounds on the probability of being detailed.[15] We bin distance in 5 kilometer increments up to 50 kilometers away from an AMC, and 25 kilometer increments up to 300 kilometers away from an AMC. We include a separate bin for physicians in the same zip code as an AMC, and an additional division at 2.5 kilometers from the AMC.[16] In the empirical tests of differential effects (Equation (10)), we use the same exogenous variable/instrument for detailing as before: the binned log 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 information channel measure.

In each case, the vector X_{it} includes whether the physician is male, years since graduating medical school in ten-year increments, indicators for whether the physician attended a top-25 or top-100 medical school, 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), and patient-mix composition controls.[17] We also include the 9-category urban/rural continuum

[14]Grennan et al. (2024) use a different aggregation of the same underlying source. In their paper, they instrument for detail propensity using the weighted AMSA conflict of interest score in the physicians' hospital referral region (excluding scores at their own hospital service area and hospital).

[15]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.

[16]We choose the bin size to scale with how quickly the detailing probability changes with distance (see Figure 3b). The exact specification of the bin size has little quantitative effect on the results.

[17]About 2.5% of observations are dropped due to missing physician characteristics. Results are consistent

codes, market size, physician peer network size, and year fixed effects, λ_{dt}. Each regression is estimated separately for each drug d, and standard errors are clustered at the physician level.

4.2.2 Results

Awareness

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 yields two predictions about physician responses in this dimension. First, detailing will have an effect on the extensive margin (whether or not a physician writes any prescription for the drug) for physicians who were previously unaware of the drug. And second, the effects of detailing should be smaller for previously aware physicians relative to those who were unaware. Accordingly, we estimate Equation (9) for physicians who have not prescribed the drug in the past (potentially unaware) and estimate Equation (10) where the information channel is an indicator for whether the physician has prescribed the drug in the past.

Table 3 presents the point estimates and standard errors for each estimation. Figure 4 provides a visualization of these results. In both the table and figure, panel A corresponds to the extensive margin test (Equation (9)) and panel B corresponds to the differential effect of detailing on prescription shares by previous prescription history (Equation (10)).

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with an alternative specification on the full sample that excludes physician characteristic controls. 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.

Figure 4a shows that the extensive margin responses to detailing among physicians with no previous prescriptions are positive for all drugs in the sample and statistically significant for all but one. For most drugs in the sample, physicians with no previous prescription history are between 13 and 30 percentage points more likely to prescribe the drug after a detailing visit. This finding is consistent with the idea that detailing increases the awareness of a drug.

However, our model also predicts that previously aware physicians will respond less to detailing visits relative to otherwise similar but unaware physicians. Figure 4b shows that this pattern is not present in the data. In fact, we find a positive and statistically significant interaction term for all drugs in the sample. Physicians who have previously prescribed the drug increase prescribing *more* in response to a detailing visit then observably similar physicians that have not prescribed the drug before.

While the extensive margin responses are consistent with the model of information via awareness, the difference in prescription share responses are not. Responses to detailing are the greatest for physicians that we know are already aware of the drug. Moreover, for the majority of drugs, the effect of detailing on the prescription share for physicians with no previous prescription history is negative (panel B in Table 3). Together with the extensive margin results, this suggests that physicians without a previous prescription history that do not receive a detailing visit are less likely to prescribe the drug but prescribe more of it when they do.

Experience and Mean Beliefs

We next turn to testing physician response predictions (ii) and (iii) from section 2.1. Our model predicts that more experienced physicians (i.e., those with less uncertainty about the drug quality) should increase their prescriptions less than otherwise similar physicians with less experience. And, physicians with higher mean prior beliefs about the drug's quality will

increase their prescriptions less than those with lower prior beliefs.

Accordingly, we estimate Equation (10) where the information channel is a measure of experience (lagged 365-day prescription supply) and again where the information channel is a measure of prior beliefs (lagged benchmark residual). The results are displayed in Table 4 and Figure 5.

If our stylized model of information exchange explains real world physician responses to detailing, the estimated interaction between detailing and either experience or prior beliefs should be negative. We find the opposite. Physicians with more experience prescribing the drug have greater responses to detailing visits, and physicians with higher mean beliefs (i.e. those that prescribe more relative to their benchmark predicted share) have higher positive responses to detailing visits.

Response over Time

A final prediction from our model is that there are diminishing information returns from detailing. As physicians learn more about the drug (through detailing or other channels), informative effect of detailing will fall over time.

We empirically test this prediction by estimating Equation (11), where τ denotes year since drug entry. 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 estimate the share 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. Results are presented in Table 5 and Figure 6.

$$RxShare_{idt} = \left(\sum_{\tau} \beta_{d\tau} \mathbb{1}(t = \tau) \right) D_{idt} + X'_{it}\gamma_d + \lambda_{dt} + \epsilon_{idt} \tag{11}$$

We find the effect of detailing does not fall over time. In nearly every case, the response

of detailing increases with each year following entry.

When taken altogether, we interpret the findings of this section to be evidence against information as a key mechanism in the physician response to detailing. While it is possible that information provision is part of the process through which detailing encourages more prescriptions, the data provide little support for the predictions from the model of learning. Rather, our results suggest that other kinds of advertising effects, such as prestige or brand loyalty, are likely driving physician responses.

4.3 Firm Detail Visit Targeting

4.3.1 Empirical Specifications

In Section 2.2, we present a model in which profit maximizing firms will target their detailing visits to physicians with the highest expected response to detailing, conditional on patient volume. We argue that if firms believe information exchange is a key mechanism 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 is a driving mechanism, then firms will target physicians that (i) are previously unaware of the drug , (ii) have less experience with/ high uncertainty about the drug, (iii) have low prior mean beliefs about the drug, 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:

$$D_{idt} = \alpha_d^{det} D_{id,t-1} + \alpha_d^{exp} \text{Experience}_{id,t-1} + \alpha_d^{bel} \text{Belief}_{id,t-1} + f_d(V_{idt}) + \Gamma_d X_{it} + \Lambda_{dt} + \nu_{idt} \tag{12}$$

We assess whether a physician i is less likely to being detailed in year t if they were detailed for that drug in the previous year ($D_{id,t-1}$), if they had more experience prescribing

the drug in the previous year (Experience$_{id,t-1}$), and if they had high beliefs about drug quality (i.e., over-prescribing relative to his/her patient-mix-adjusted benchmark level) in the previous year (Belief$_{id,t-1}$).

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-mix composition, and physician characteristics. We include county fixed effects to account for the possibility that detailing costs vary by region. Moreover, we include two controls to capture potential complementarities in detailing groups of physicians: an indicator for whether another physician in the same zip code was detailed and an indicator for whether another physician at the same address was detailed. In Section 4.4, we estimate the model with zip code fixed effects and find similar results.

We also control for a measure of the number of peer physicians, which Agha and Zeltzer (2022) find is a factor in the detail targeting decision.[18] We estimate the model for each drug separately, and cluster standard errors at the physician level.

4.3.2 Results

The results for the key coefficients of interest (α_d^{det}, α_d^{exp}, and α_d^{bel}) are displayed in Table 6 and Figure 7. 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 show that each of these

[18]Following Agha and Zeltzer (2022), we use the number of shared patient linkages as a measure of the number of peer physicians. We construct the measure using the 2015 Physician Shared Patient Patterns Data.

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.

Across all drugs, firms are more likely to detail physicians that they have already detailed for that drug in the past. On average, firms are about 40 percentage points more likely to detail physicians they have already detailed than visit new physicians with similar volume, patient characteristics, and location. They are also more likely to detail physicians that have more previous experience with the drug and thus have less uncertainty about the drugs' quality. Finally, 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, though this is only statistically significant at the 5% level for four of the drugs. We note there are two firm-drug pairs that appear to target under-prescribers of the drug, Basaglar and Tymlos.

Next, we test whether the detail targeting policies of firms are more focused on the less informed physicians in the initial years following entry as the model predicts that returns to information decline over time. We estimate the same policy function as in Section 4.3 but allow the parameters for previous detailing, experience, and beliefs to vary by year following entry. The results are presented in Table 7.

We find that for three out of eight drugs, firms are more likely to target under prescribers in the first year of detailing, compared to only two out of eight drugs in the second year of detailing. While this is consistent with firms focusing more on information provision in the initial years of the detailing campaign, the other results are to the contrary. In fact, for seven out of eight drugs, detail visits are most strongly correlated with lagged prescription volume and lagged detail visits in the first year following the entry of the drug.

Importantly, we note that the firm targeting policies *are* consistent with the firm model presented in Section 2.2 and the evidence on physician responses in Section 4.2. Firms are

targeting the physicians that have the greatest responses to detailing, but we show that these are *not* the same physicians that would be expected benefit from and respond to information and learning.

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 4.2, we believe these results suggest that the prescription response to detailing is due to other kinds of advertising effects rather than direct provision of information, which we discuss in Section 5.

4.4 Robustness and Heterogeneity

The conclusion from our empirical tests is that the data patterns for physician responses to and firm targeting of detail visits are not consistent with a model of information. It is important for the interpretation of these results that the data patterns we illustrate are general, rather than the result of our empirical specifications. In this section, we test the robustness of these results in several ways.

First, we estimate all of the main results of the paper on an extended sample of drugs. This includes eight drugs that meet the criteria of pursuing large detail campaigns during the sample period but address more narrow chronic indications for which it is harder to observe the target population. In many cases, the drugs are meant to be prescribed along side other treatments. We provide more detailed information about these drugs in Appendix Table A2. The results of our estimations are displayed in Appendix Tables A3, A4, and A5.

The results of estimation on this extended sample are qualitatively similar to those presented in the main analysis. Physician without any previous prescriptions respond on the

extensive margin in their prescriptions, but at smaller magnitudes than the main drugs studied. And, the greatest responses to detailing are among physicians with any previous prescription history, greater volume of prescriptions in the previous year, and more prescriptions relative to the expert benchmark. Similarly, firms are more likely to target physicians that they have detailed before and have more experience with the drug. For three out of eight drugs in this sample, firms are slightly more likely to target physicians that under-prescribe relative to the expert benchmark. Across this sample, magnitudes are very small and often not statistically different from zero.

Next, we re-estimate the main results of the paper using alternative samples of physicians. Appendix Figures A1 and A2 illustrate how four alternative sample estimations compare to the baseline estimates for physician responses: "Accepts Detail", "Main Specialty", "Non Main Specialty", and "Single Cross Section".

The "Accepts Detail" sample considers only physicians that ever receive a detail visit for any drug or device in the OpenPayments data. Because some physicians consider accepting visits from industry representatives as a conflict of interest, they may refuse these visits. In our estimation, these physicians are never takers with the respect to the instrument shifting detailing propensity. When we exclude these physicians, the estimates are quantitatively similar.

The "Main Specialty" and "Non Main Specialty" samples divide the physicians into two groups: those that are a member of the main prescribing specialty for a given drug (e.g. pulmonologists for the COPD drugs) and those that are not. The large majority of physicians that are not part of the main specialty practice some form of primary care, i.e. internal medicine, family medicine, or physician assistants. The qualitative data patterns are similar between the two groups and reinforce the primary conclusion of the baseline empirical exercise. Neither group exhibits data patterns that would be consistent with learning or information being the primary mechanism of detailing visits.

The "Single Cross Section" sample displayed in Appendix Figure A1 estimates the awareness channel tests using only a single year of data. We include this robustness check to address the concern that our indicator for any previous prescription by the physician is an absorbing state. Thus, the composition of the sample in Appendix Figure 4a changes over time and physicians permanently switch from the no previous prescription to the previous prescription group in Appendix Figure 4b. This could confound the results in this estimation with other time trends in the effect of detailing. To address this, we re-estimate the specification using only a single cross section of data, corresponding to the second year following entry of each drug, which is the most recent year available for all the drugs in the sample. Reassuringly, we find the same qualitative results.

Appendix Figure A3 displays the results of the firm targeting estimation specifications for four robustness specifications: "Accepts Detail", "Main Specialty", "Non Main Specialty", and "Zip Code Fixed Effect". The first three are re-estimations of the firm targeting specifications under the physician samples described above. The "Zip Code Fixed Effect" estimation replaces the county-level fixed effects with zip code level fixed effects.

Across all of these specifications, the results of the firm targeting policies are quantitatively similar. Some exceptions appear in the detailing policy for physicians in the main specialty. The coefficients on the relationship between detailing and the lagged benchmark residual among specialists are not statistically different from zero for many drugs due to large standard errors. This is a result of much smaller variation in these residuals among specialists. Similarly, the targeting policies are less dependent on prescription volume and, for several of the drugs, do not appear related at all. However, that the lack of a statistical relationship between detailing visits and lagged prescription volume among specialists still does not provide evidence in support of the model of information presented in Section 2, which would predict a negative relationship.

We next consider whether the increase over time in physician response to detail visits can

be attributed to new information released about the drug. During the sample period, four of the drugs were approved for label changes. These are typically the result of some post-market clinical trials that reveal new, relevant information about the drug. For example, the Tresiba label was updated in 2018 after additional trials demonstrated that the drug did not increase the risk of adverse events for people with high cardiovascular risk. New information could account for the rising responses to detailing over time and complicate the predictions of the model. To check whether the new information can explain the rising responses to detailing, we plot the detailing effects over time and separately indicate which drugs receive approval for a label change in which years (Appendix Figure A4). Drugs without any label changes show similar trends in the rising response to detailing, and the drugs with label changes do not show diminishing responses before nor after the post-market approvals.

Finally, we consider two different approaches to testing how physician responses depend on their prior beliefs. The results are displayed in Appendix Table A6. First, we re-estimate the benchmark model using expert prescriptions in the same year rather than expert prescriptions in the latest year of the sample (Panel A). We find the same qualitative results. Second, we re-estimate the specification allowing the slope of the detailing effect to be different for physicians with a positive residual and those with a negative residual (Panel B). This allows for the possibility that under- and over-prescribers of the drug might respond differently to a detailing visit. For all drugs, over-prescribers have a significant and positive interaction, i.e. physicians that over prescribe by more respond less to detailing. For under-prescibers, two of the drugs show no statistically significant relationship between the benchmark residual and the effect of detailing. Because the prediction of the model in Section 2 is that the slope of this effect should be negative for both under and over-prescribers, we view these results as inconsistent with the model in Section 2 and in line with the other data patterns we demonstrate.

5 Discussion & Alternative Explanations

We have now presented a set of empirical facts which do not appear to support the model 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 and information.

This naturally raises two questions. First, what model *does* explain the data? 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 alternative 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

Consider a model in which physicians have some drug-patient-specific preference given by δ_{ip}, and these preferences (which potentially include beliefs about drug quality) do not update in response to a detailing visit. Instead, physicians respond to detailing visits through the direct utility effect, θ_i.

$$u_{ip}(D_i) = \theta_i D_i + \delta_{ip}, \tag{13}$$

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 explains why products that are widely known with relatively consistent characteristics still advertise, i.e. Coca-cola and Pepsi. We interpret θ_i as being unrelated to benefits to the patient, and therefore potentially creating a wedge between consumer welfare and physician decision making.

By allowing θ_i to be fully flexible, it is easy to see how this model can replicate *any* patterns we see in the data. This makes it difficult to locate any specific patterns that suggest this kind of direct utility effect is the right model for the data. However, DellaVigna and Gentzkow (2010) propose two pieces of evidence for "preference-based" persuasion in a general advertising context. The first is that advertising recipients (i.e., the physicians) may take costly steps to avoid advertising. In the case of pharmaceutical detailing, AMCs take the step to enforce conflict of interest policies that limit the ability of affiliated physicians to accept detailing visits (see Figure 3). This is clear evidence that some groups of physicians believe detailing to be potentially harmful, or a potential source of an unwanted distortion in their behavior, and take steps to avoid exposure.

Second, because consumption and advertising are complements, the level of consumption should increase the marginal utility of advertisements (DellaVigna and Gentzkow, 2010). For example, Ford truck owners like to see Ford advertisements, which make them feel even happier about their decision to use Ford trucks. To see the analogy in our setting, notice that physicians receive the warm-glow effect from advertising for each prescription that they make. If they are prescribing more of the drug to begin with, they will receive a greater benefit from the advertising. While we cannot directly test this complementarity in utility, our results are consistent with this mechanism. Physicians with more experience and physicians that over-prescribe the drug relative to their peers have greater prescription responses from being detailed (see Table 4). Pharmaceutical firms know this and target high-prescribing physicians. Firms are more likely to target physicians that have been detailed in the past, have more experience, and over-prescribe relative to their peers (see Table 6).

This model can also explain the frequency of repeated detailing in the data. The physicians with the greatest response to detailing are those with the highest values of θ_i. Rather than a widespread information campaign, pharmaceutical detailing is primarily an endeavor to identify those physicians with high θ_i, and repeatedly target that segment. This view is consistent with our data. In the next section, we describe who these "high θ_i" doctors may be in terms of gender, medical school ranking, age, peer networks, and prior relationship with the firm.

5.2 Demographics of Detailing

In Table 8, we examine how detail targeting is associated with physician characteristics, i.e. which physicians have high values of θ_i. We append all physician-drug level data into one empirical sample and estimate which characteristics are associated with ever being detailed, being detailed at drug entry year, and the number of repeat visits. In all specifications we control for patient-mix characteristics, market size, physician specialty, and drug fixed-effects.[19] Standard errors are clustered at the physician-drug level.

We find that male physicians are more likely to be detailed than female physicians, even after controlling for patient characteristics, physician specialty, market size, and tenure. Conditional on ever being detailed, they are also more likely to be detailed at drug entry year and substantially more likely to receive future visits. Men are nearly 35 percentage points more likely to be detailed more than once conditional on receiving any detail visit.

Physicians who graduated from top ranked medical school are less likely to be detailed. Conditional on being detailed once, graduates from top 100 ranked medical schools are about 5 percentage points less likely to receive future visits, and graduates from the top 25 ranked medical schools are 14 percentage points less likely to receive future visits than graduates of lower ranked schools. This is consistent with these physicians being better informed but

[19]See Appendix Table A1 for summary statistics of physician characteristics, by drug.

could also be driven by more educated physicians being less receptive to advertising overall. We also find that specialists are more likely to be detailed at all, detailed first, and detailed repeatedly. This pattern likely reflects their prescription behavior more than their education or expertise.

Firms are also more likely to detail physicians that they have detailed in a prior campaign for another drug. These physicians are more likely to receive any visit, get detailed first conditional on receiving a visit, and get detailed multiple times. This is consistent with targeting physicians that are known to be receptive to brand-based advertising and a value to establishing longer term physician-industry relationships.

While firms are not more likely to ever detail physicians with large peer networks, they are more likely to detail these physicians multiple times conditional on receiving any visit at all. This finding is consistent with the work of Agha and Zeltzer (2022) which shows that detailing has spillover effects with these peer networks. This pattern of spillover effects within peers could be consistent with both information diffusion or image and prestige effects (Goldenberg et al., 2009).

Finally, we also look at differences by graduation year bins (with reference group being those that graduated after 2010). We find little relationship between getting detailed at entry and graduation year. However, we do find a hump shape in the propensity to be detailed at all and to be detailed repeatedly, with the detailing propensity peaking at physicians that are 25-35 years out of medical school, which could be related to professional status.

While some of these results may fit into our model of information, (e.g., top- educated doctors being detailed less and well-connected doctors getting detailed more), others do not. For example, the large gap in detail propensity between men and women suggests that group differences in the utility value of advertising, as described in the model above, are a better explanation of the data. Further, the large positive coefficient on *Prior Detail By Firm* suggests that persistent physician-industry relationships exist, consistent with the idea of

prestige or brand loyalty effects described in traditional models of advertising.

5.3 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 and credibility through more costly signaling (Spence, 1973). In this kind of costly signaling 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 does not fit the patterns for over-prescribing (high belief) physicians. In the costly-signaling model, the firm repeatedly targets physicians that are under-prescribing relative to full-information. However, we show that detailed physicians in the data already prescribe more relative to their peers, and firms are more likely to target the physicians that over-prescribe, even conditional on previous detailing visits to the same physician 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 provision; 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 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 more experience and those whose prior beliefs are greater than 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 who 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.

We note some important limitations. First, we do not have data on the distribution of free samples or discounts on copays, which could drive some of the effect of detailing we identify.[20] Because 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), we view this mechanism as another potential source for a wedge between physician decision making and the optimal allocation of drugs across patients. Further, while we suspect that marketing driven by prestige or reputation may not be in the best interest of the patient, we do not have data on patient outcomes to confirm. Additional analyses the directly investigate how the relationship between detailing, free samples, and health outcomes map back to patient welfare is an important area of future research.

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Tables

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.

Table 2: Summary Statistics

Drug	Scripts (thous.)	Ever Prescribe	Rx Share | Prescribe	Detail Visits (thous.)	Ever Detailed	Ever Prescribe | Detailed
Anoro	3131	0.25	0.011	442	0.14	0.64
Stiolto	733	0.08	0.006	217	0.09	0.35
Bevespi	137	0.03	0.005	193	0.06	0.17
Toujeo	1973	0.18	0.009	355	0.14	0.57
Tresiba	1981	0.20	0.009	538	0.16	0.56
Basaglar	1390	0.26	0.008	164	0.11	0.52
Tymlos	35	0.02	0.004	31	0.03	0.21
Vraylar	142	0.06	0.012	99	0.07	0.34

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.

Table 3: Physician Response to Detailing - Awareness

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Extensive Margin Response Given No Previous Prescription								
Detail	0.174***	0.129***	0.153***	0.313***	0.239***	0.163***	0.019	0.167***
	(0.014)	(0.013)	(0.021)	(0.014)	(0.012)	(0.027)	(0.015)	(0.018)
N	770103	739912	436671	627392	524239	404768	423195	258245
Panel B: Differential Share Response by Awareness (Lagged Prescription Indicator)								
Detail	-1.115***	-0.462***	-0.285	0.844***	0.409***	-0.671***	-0.777***	-0.225
	(0.278)	(0.152)	(0.284)	(0.097)	(0.102)	(0.194)	(0.249)	(0.439)
Interaction	7.495***	3.629***	5.428***	3.277***	4.642***	10.710***	3.215***	7.890***
	(0.169)	(0.114)	(0.307)	(0.071)	(0.083)	(0.217)	(0.311)	(0.474)
N	814880	753986	438923	666022	545293	420137	423619	260581

Note: Physicians without any prior prescription history respond to detailing. Each column contains the estimates for a particular drug. Panel A contains the estimates for the extensive margin response—additional probability of prescribing the drug to any patients—for physicians without any previous prescription history of the drug (Equation (9)). Panel B contains the estimates of the effect of detailing on the prescription share response—additional share of patient-days that are prescribed the drug, measured in percentage points—interacted with whether the physician has a previous prescription history (Equation (10)). Each estimation includes controls for year, physician characteristics, and patient-mix. Statistical significance is based on clustered standard errors at the physician level, with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Differential Response by Experience and Beliefs

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Experience (Lagged 365-Day Supply)								
Detail	-1.192	-3.513***	-2.552	2.851**	-0.474	-12.813***	-1.233	3.601
	(0.800)	(1.112)	(1.887)	(1.311)	(2.376)	(1.954)	(0.770)	(3.196)
Interaction	0.682***	0.666***	1.039***	0.450***	0.629***	2.404***	0.938***	1.500***
	(0.039)	(0.056)	(0.303)	(0.056)	(0.096)	(0.260)	(0.226)	(0.270)
N	44254	13953	2250	37989	20797	15357	424	2301
Panel B: Mean Beliefs (Lagged Benchmark Residual)								
Detail	2.449**	1.629	0.937	-1.938	-2.414	-9.392***	-0.572	-3.792
	(1.057)	(3.206)	(1.737)	(2.400)	(2.227)	(2.553)	(0.553)	(3.059)
Interaction	3.068***	0.742***	3.572***	1.486***	2.438***	5.863***	1.265***	5.203***
	(0.161)	(0.193)	(0.846)	(0.186)	(0.221)	(0.861)	(0.103)	(0.334)
N	44254	13953	2250	37989	20797	15357	424	2301

Note: This table presents the estimation results of prescription share 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 in Equation (10) using a different term for $InfoChannel$. In Panel A, we use experience measured by lagged annual prescription supply. In Panel B, we use mean beliefs measured by the distance in standard deviations from the lagged benchmark residual. Each estimation includes controls for year, physician characteristics, and patient-mix. Statistical significance based on clustered standard errors by physician with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Physician Response to Detailing By Year

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Detail×	0.427**	0.127***	0.056***	0.498***	0.780***	0.713***	-0.070	0.761***
Year 0	(0.190)	(0.031)	(0.020)	(0.039)	(0.053)	(0.059)	(0.068)	(0.149)
Detail×	0.445***	0.188***	0.229**	0.927***	1.091***	0.388**	0.010	0.850***
Year 1	(0.148)	(0.051)	(0.095)	(0.057)	(0.068)	(0.160)	(0.066)	(0.200)
Detail×	0.725***	0.387***	0.613**	1.861***	1.701***	0.949***	0.206*	1.516***
Year 2	(0.122)	(0.075)	(0.293)	(0.105)	(0.114)	(0.245)	(0.118)	(0.277)
Detail×	1.409***	0.376***		2.309***	3.047***			2.315***
Year 3	(0.180)	(0.110)		(0.138)	(0.192)			(0.324)
Detail×	2.944***	1.067***		2.916***				
Year 4	(0.401)	(0.208)		(0.179)				
Detail×	4.248***							
Year 5	(0.512)							

Note: The effect of detailing on whether a physician writes any prescription for a drug is increasing over time. Each column represents an estimation of Equation (11). The coefficients display the total effect in each year, i.e. the third row displays the effect of detailing two years after drug entry. Each estimation includes controls for year, physician characteristics, and patient-mix. Statistical significance is based on physician clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Firm Detailing Behavior

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Lag Detail	0.530***	0.470***	0.258***	0.506***	0.593***	0.485***	0.441***	0.489***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)
Lag Experience	0.007***	0.010***	0.015***	0.015***	0.007***	0.003***	0.055***	0.029***
	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.007)	(0.003)
Lag Belief	0.013***	0.008***	-0.001	0.005***	0.002*	-0.003***	-0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Note: Firms are more likely to detail previously detailed, more experienced, and over-prescribing (higher mean belief) physicians. This table presents coefficients from the linear probability model specified in Equation (12). We regress detail visits (D_{idt}) on prior year detailing, an experience measure (lagged annual supply), a belief measure (lagged residual to benchmark prescription rate), and other controls for year, physician characteristics, and patient-mix. Each column represents results from a drug-specific regression. Statistical significance is based on physician clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Firm Detailing Behavior By Year

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Lag Detail								
× Year 1	0.605***	0.577***	0.284***	0.677***	0.679***	0.557***	0.630***	0.530***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.010)	(0.008)
× Year 2	0.647***	0.540***	0.248***	0.478***	0.641***	0.457***	0.400***	0.453***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.003)	(0.004)	(0.007)	(0.008)
× Year 3	0.584***	0.496***		0.483***	0.519***			0.525***
	(0.003)	(0.004)		(0.004)	(0.004)			(0.009)
× Year 4	0.420***	0.337***		0.451***				
	(0.004)	(0.005)		(0.005)				
Experience (Lagged 365-Day Supply)								
× Year 1	0.029***	0.069***	0.090***	0.033***	0.029***	0.022**	-0.062	0.048***
	(0.006)	(0.013)	(0.013)	(0.004)	(0.003)	(0.009)	(0.083)	(0.012)
× Year 2	0.007***	0.022***	0.012***	0.018***	0.014***	0.004***	0.078***	0.033***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.008)	(0.005)
× Year 3	0.011***	0.014***		0.019***	0.007***			0.024***
	(0.001)	(0.002)		(0.001)	(0.001)			(0.003)
× Year 4	0.012***	0.013***		0.018***				
	(0.001)	(0.002)		(0.001)				
Mean Beliefs (Lagged Benchmark Residual)								
× Year 1	-0.017***	0.011***	0.000	-0.006**	-0.005***	-0.003	0.000	0.005***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
× Year 2	0.008***	0.010***	-0.001	0.012***	0.005***	-0.003**	-0.004***	0.007***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
× Year 3	0.023***	0.012***		0.010***	0.010***			-0.004***
	(0.002)	(0.001)		(0.002)	(0.002)			(0.002)
× Year 4	0.033***	0.007***		0.005**				
	(0.002)	(0.001)		(0.002)				

Note: The estimations follow the same specification as Table 6 but allows the three coefficients of interest in Equation (12) (experience, beliefs, and lag detailing) to vary by year. The coefficients display the total effect, i.e. the second row displays the increase in detailing propensity associated with having been previously detailed in the second year following following entry. We only display coefficients for the first four years following entry. Statistical significance is based on physician clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

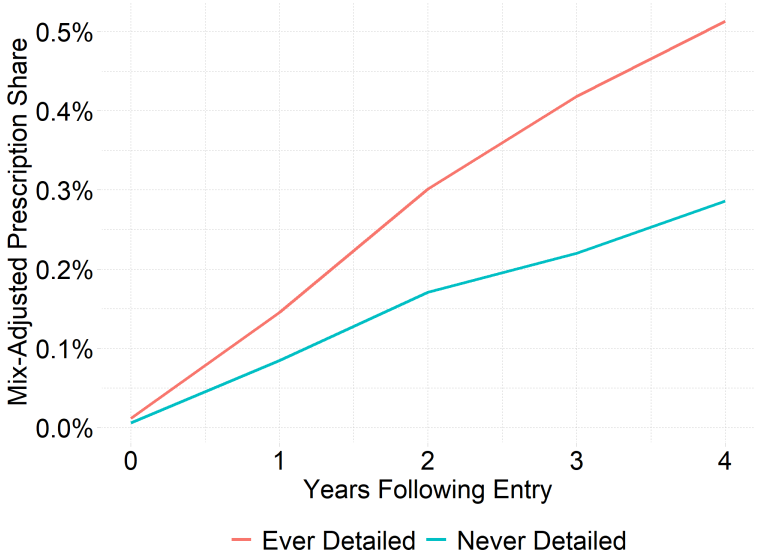
Table 8: Detailing Patterns and Physician Characteristics

	Ever Detail	Detail at Entry	Number of Repeat Visits
Specialist	0.262***	0.095*	0.824***
	(0.044)	(0.030)	(0.015)
Male	0.043**	0.018**	0.348***
	(0.011)	(0.005)	(0.012)
Top 25 School	−0.026**	−0.005	−0.088***
	(0.006)	(0.006)	(0.017)
Top 100 School	0.007	−0.001	−0.049***
	(0.005)	(0.002)	(0.008)
Peer Network Size	0.040	0.003	0.162***
	(0.018)	(0.008)	(0.012)
Prior Detail By Firm	0.506***	0.300***	0.133***
	(0.061)	(0.028)	(0.008)
Grad 2000-10	−0.001	0.009	0.100***
	(0.007)	(0.015)	(0.025)
Grad 1990-00	0.030*	0.026	0.235***
	(0.011)	(0.019)	(0.025)
Grad 1980-90	0.051*	0.042	0.241***
	(0.016)	(0.022)	(0.025)
Grad 1970-80	0.037*	0.049	0.050
	(0.014)	(0.023)	(0.026)
Grad 1960-70	0.004	0.052	−0.236***
	(0.015)	(0.024)	(0.034)
Grad 1950-60	−0.042*	0.110*	−0.371***
	(0.017)	(0.036)	(0.084)
Pat Char	Y	Y	Y
Drug FE	Y	Y	Y
N	966258	177059	177059

Note: This table presents the relationship between detailing propensity and physician characteristics. The dependent variables in each column are whether a physician is ever detailed, detailed at entry (conditional on ever being detailed), and detailed more than once (conditional on ever being detailed). Each regression includes controls for patient characteristics, market size, and specialty/expert indicators. We pool data from the 8 main drugs from our analytic samples, i.e. an observation is a physician-drug. We include drug fixed effects. The graduation year reference bin is after 2010. Standard errors are two-way clustered by NPI and drug. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.101$.

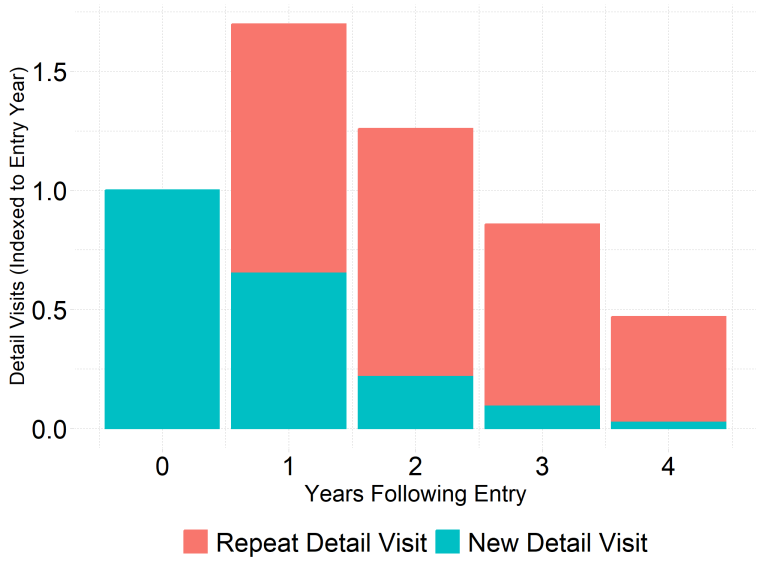
Figures

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



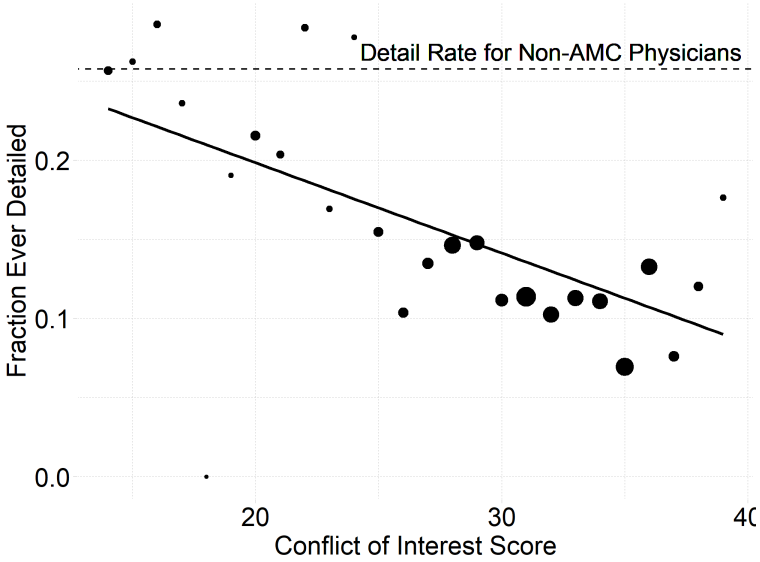
Note: Physicians that ever experience a detailing visit prescribe more of the target drug, and the prescriptions increase faster following entry. This figure shows the mean patient-mix adjusted prescription share of physicians that are ever detailed and never detailed, averaged across all drugs in the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

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

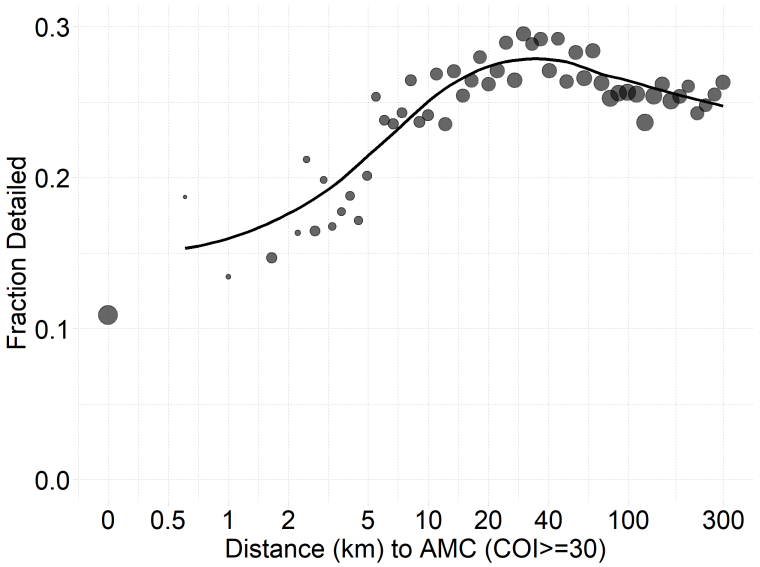


Note: Detail visits ramp up following the entry of the target drug and are primarily targeted towards the same set of physicians. This figure shows the trend in detail visits, normalized to the total number of visits in the year of entry and averaged (unweighted) across all 8 drugs in the sample. In 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).

Figure 3: Fewer Doctors are Detailed near High COI Institutions



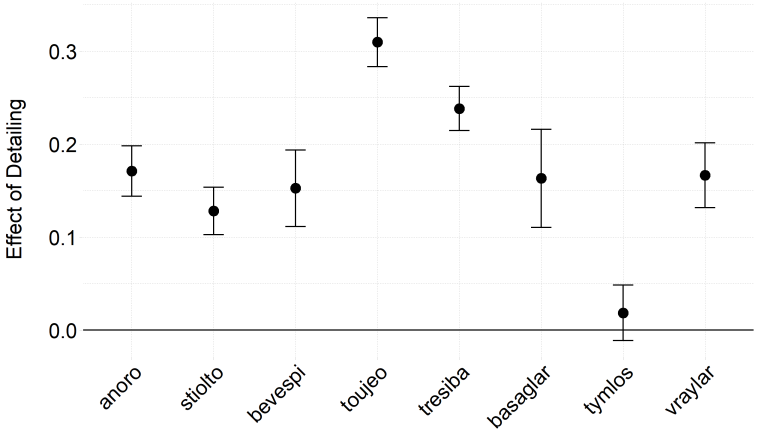
(a) High COI Institutions Detailed Less



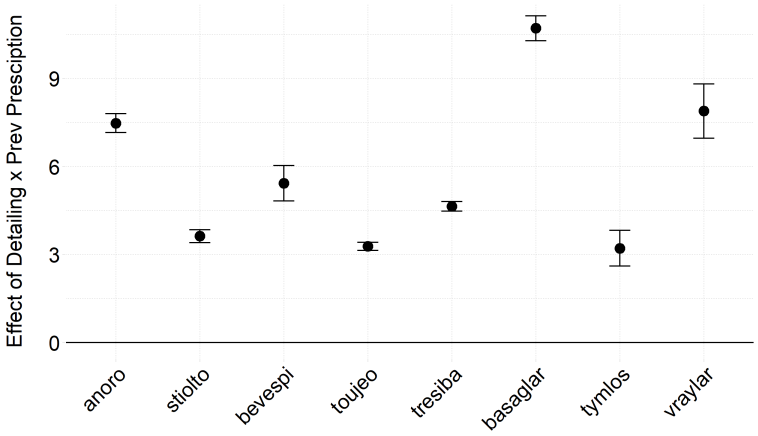
(b) Detailing Probability Increases with Distance

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.

Figure 4: Physician Response to Detailing - Awareness



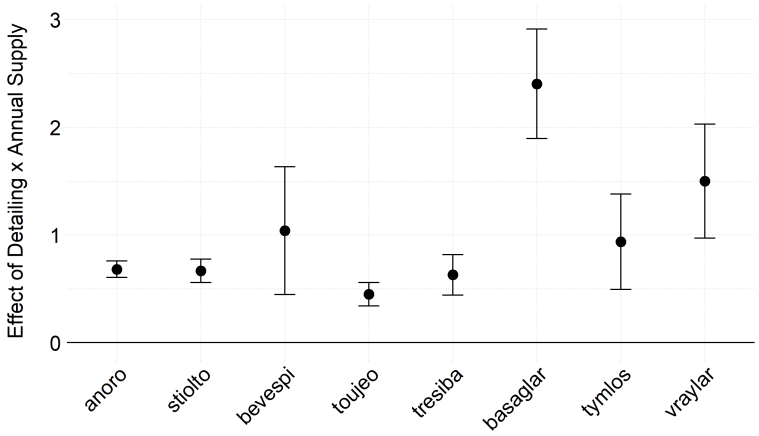
(a) Any Prescription Given No Previous Prescription



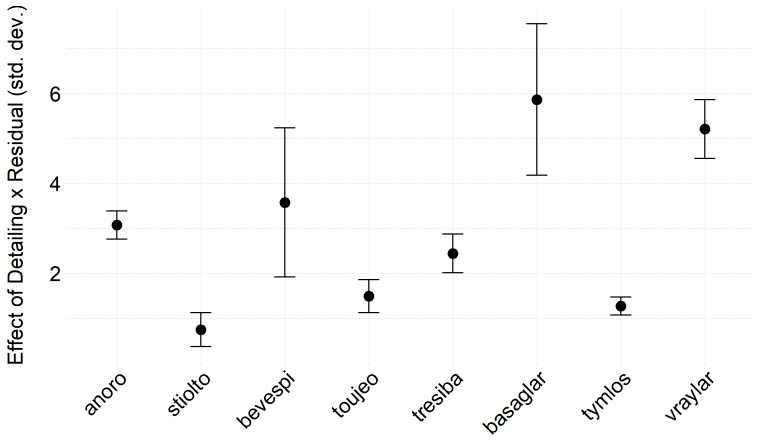
(b) Differential Share Response by Awareness

Note: Physicians without any prior prescription history respond to detailing, but there is no evidence of larger response compared to those with prior prescriptions. This figure plots the results in Table 3. Panel (a) displays the estimates for the extensive margin response—additional probability of prescribing the drug to any patients—for physicians without any previous prescription history of the drug (Equation (9)). Panel (b) displays the estimates of the difference in the prescription share response—additional share of patient-days that are prescribed the drug, measured in percentage points—between physicians with and without a previous prescription history (Equation (10)). Both panels show the 95% confidence intervals around the point estimates.

Figure 5: Differential Response by Experience and Beliefs



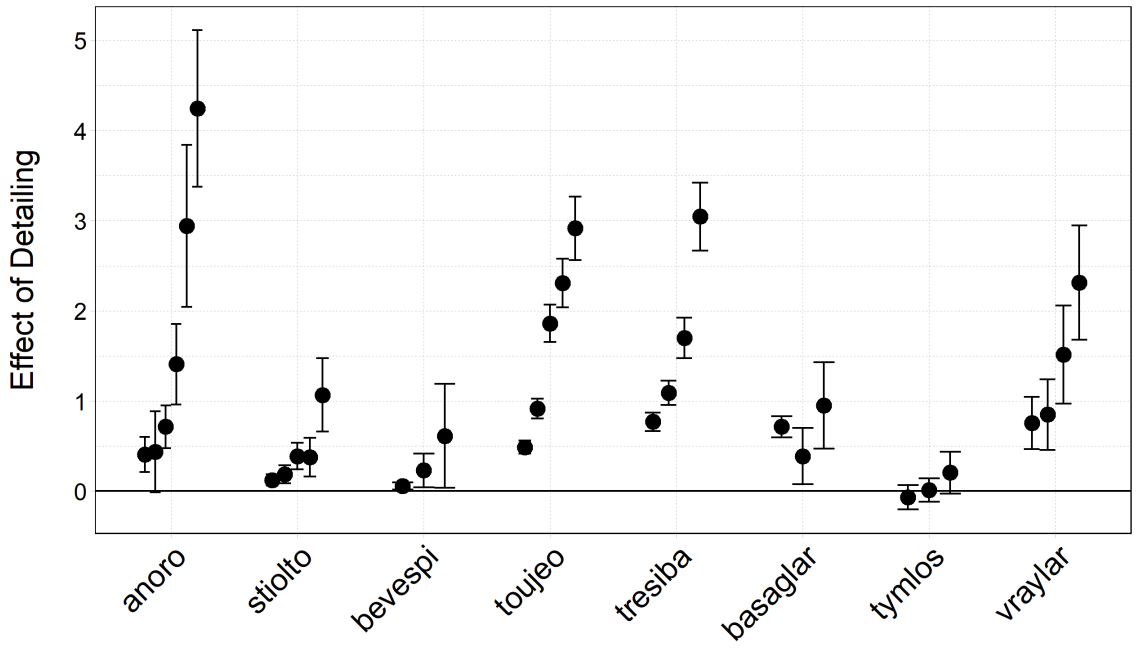
(a) Lagged Experience



(b) Lagged Mean Beliefs

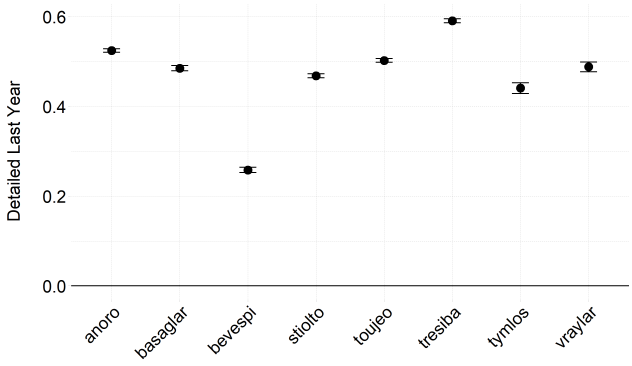
Note: This figure plots the prescription share responses by experience and prior beliefs, corresponding to the interaction terms estimated in Equation (10) and presented in Table 4. Panel (a) displays the estimates for the interaction between being detailed and the lagged annual supply of the drug. Panel (b) displays the 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.

Figure 6: Physician Responses Over Time

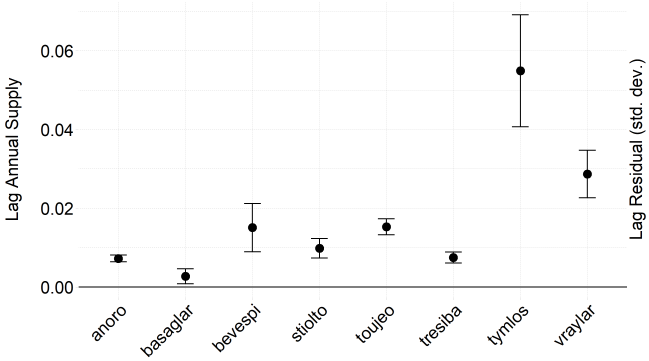


Note: This figure plots the prescription share responses to detailing over time, corresponding to those in Table 5. We plot the point estimates for the total effect of being detailed in each the year following entry of the drug (Equation (11)). Within each drug, the point estimates for each year between entry and 2019 are plotted from left to right. The standard error bars denote 95% confidence intervals.

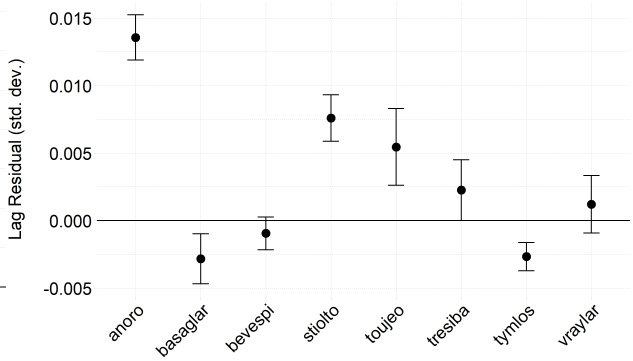
Figure 7: Firm Detailing Behavior



(a) Prior Year Detailed



(b) Prior Year Experience



(c) Prior Year Mean Beliefs

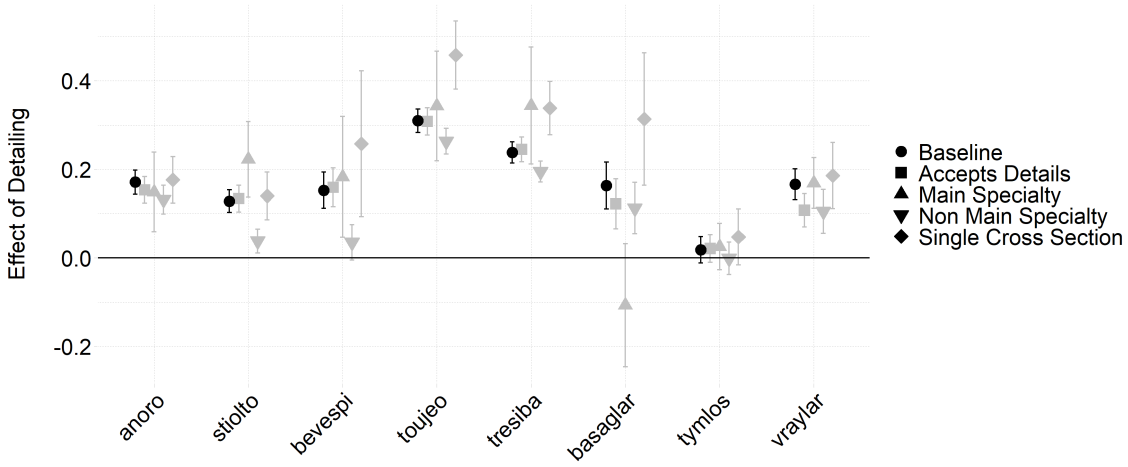
Note: These figures present the results of the firm target estimations (Equation (12)) presented in Table 6. The three panels represent three coefficients from a single estimation per-drug. Panel (a) displays the additional probably of detailing a physician with an additional annual supply prescribed 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.

Appendices

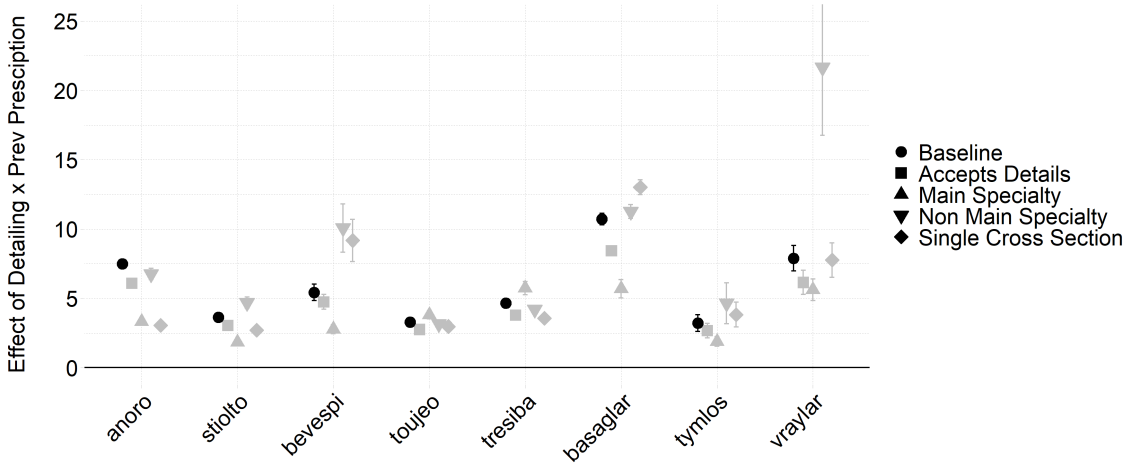
The Role of Information in Pharmaceutical Advertising: Theory and Evidence
Marquardt and Ryan (2025)

A Additional Tables and Figures

Figure A1: Physician Response to Detailing - Awareness
Robustness Specifications



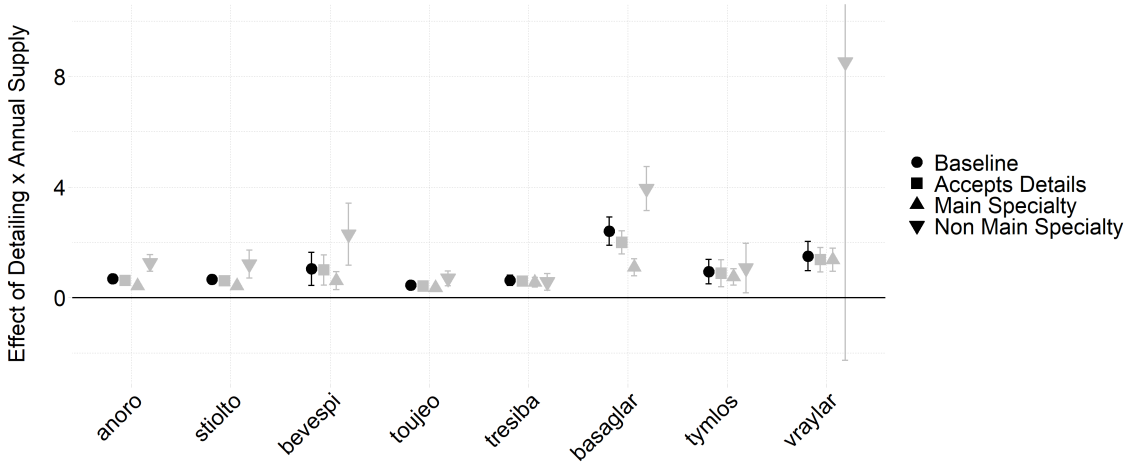
(a) Any Prescription Given No Previous Prescription



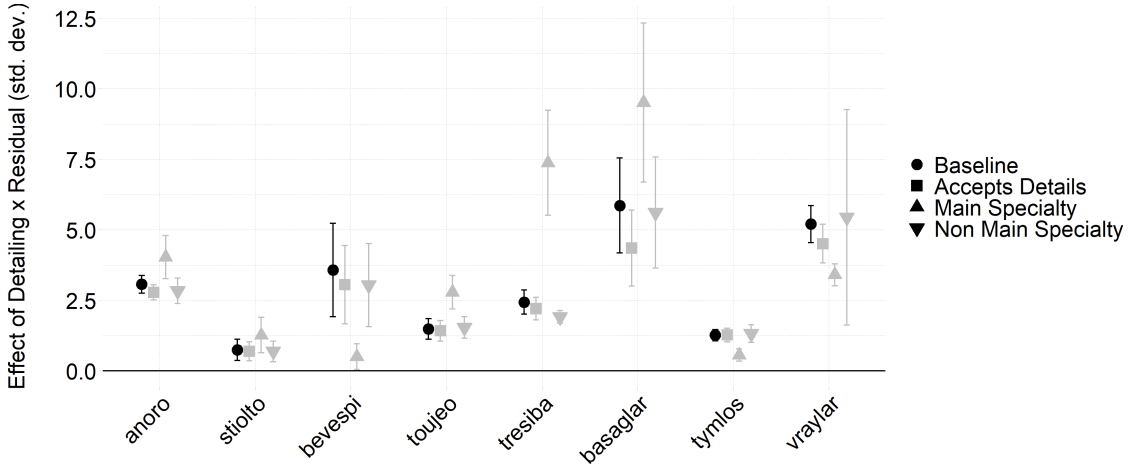
(b) Differential Share Response by Awareness

Note: This figure plots the results displayed in Figure 4 alongside estimations of the same equations for different physician samples. In each panel, we display the estimates for the baseline sample, physicians that ever accept *any* detail visit, physicians in the main specialty, physicians in other specialties, and a single cross section using data two years following drug entry. Both panels show the 95% confidence intervals around the point estimates.

Figure A2: Differential Response by Experience and Beliefs
Robustness Specifications



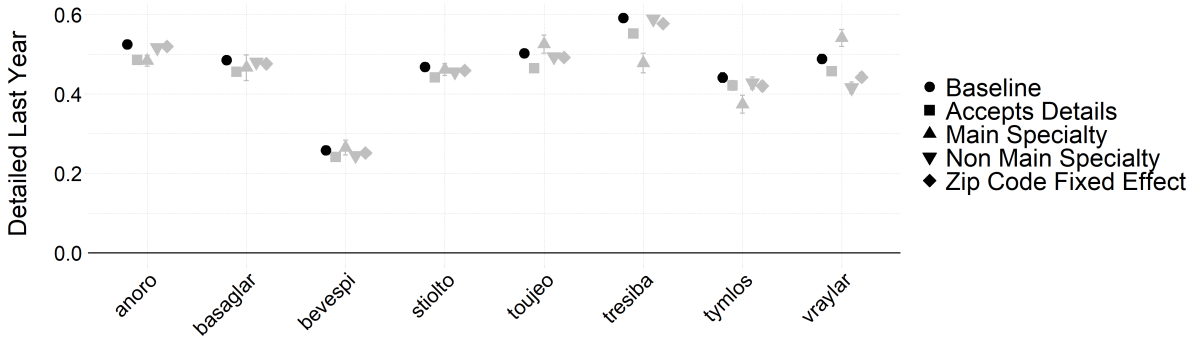
(a) Lagged Experience



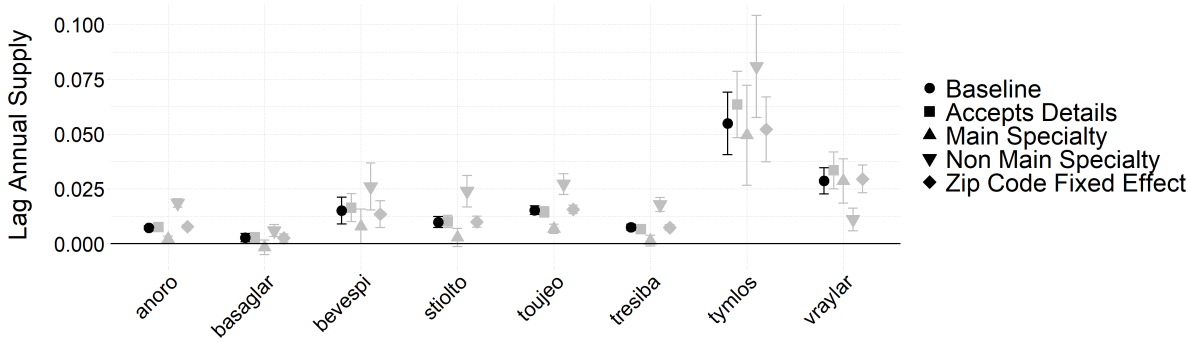
(b) Lagged Mean Beliefs

Note: This figure plots the results displayed in Figure 5 alongside estimations of the same equations for different physician samples. In each panel, we display the estimates for the baseline sample, physicians that ever accept *any* detail visit, physicians in the main specialty, and physicians in other specialties. Both panels show the 95% confidence intervals around the point estimates.

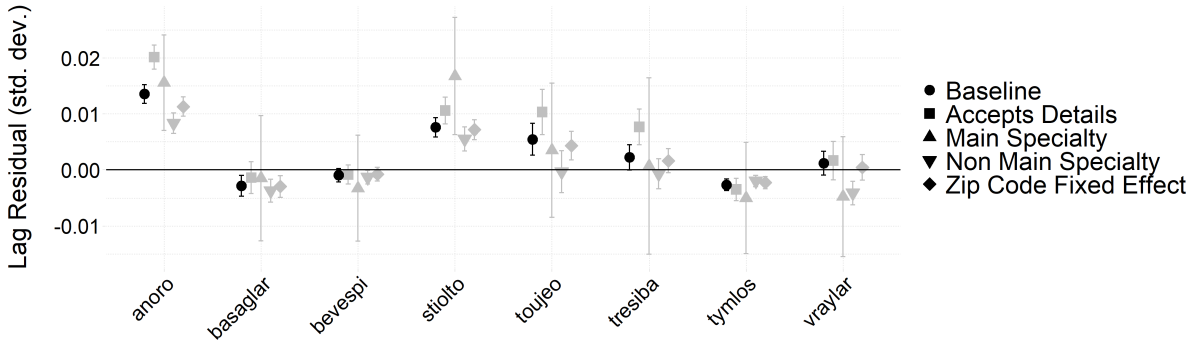
Figure A3: Firm Detailing Behavior



(a) Prior Year Detailed



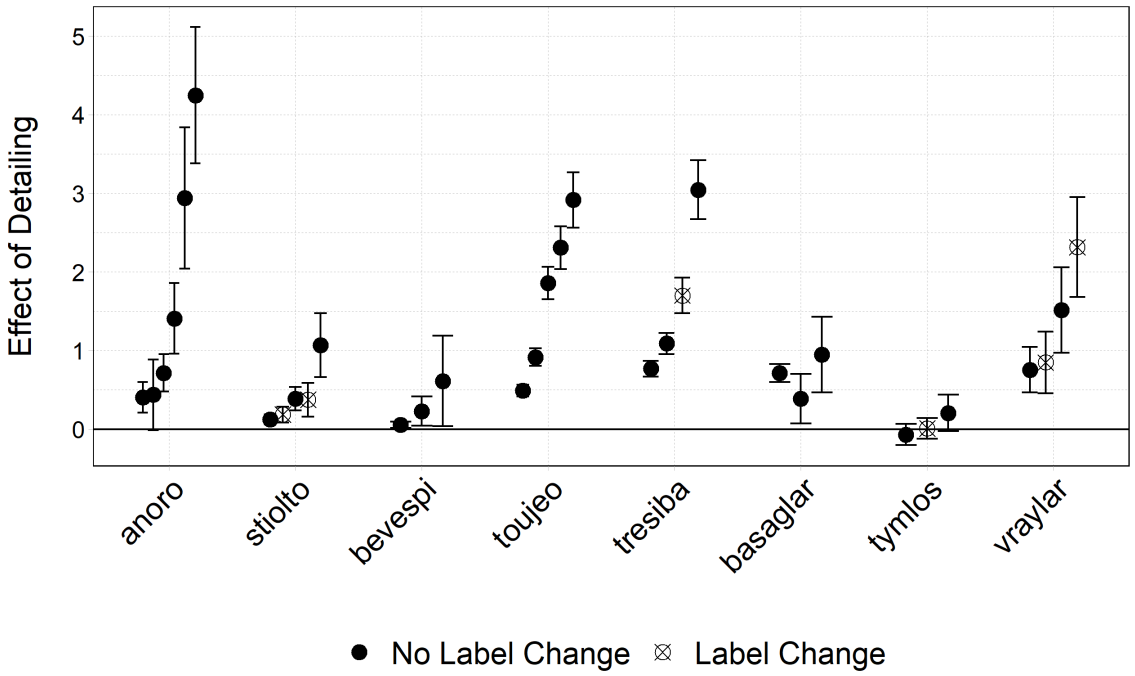
(b) Prior Year Experience



(c) Prior Year Mean Beliefs

Note: This figure plots the results displayed in Figure 7 alongside estimations of the same equation for different physician samples and specifications. In each panel, we display the estimates for the baseline sample, physicians that ever accept *any* detail visit, physicians in the main specialty, and physicians in other specialties. We also include an estimation that uses zip code fixed effects instead of county fixed effects. The standard error bars denote 95% confidence intervals.

Figure A4: Physician Responses Over Time with Label Change Indications



Note: This figure plots the same estimates as shown in Figure 6, but with an indication for years in which the FDA approved a label change for the drugs. Crossed circles indicate years in which the drugs were approved for a label change, indicating potentially new information. The standard error bars denote 95% confidence intervals.

Table A1: Summary Statistics of Physician Characteristics

	Anoro	Basaglar	Bevespi	Stiolto	Toujeo	Tresiba	Tymlos	Vraylar
% Main Specialty	5.3	2.4	4.7	4.6	2.5	2.4	5.2	7.5
% Male	60.0	51.5	53.1	59.5	55.9	53.5	55.9	60.6
% Top 25 School	6.4	5.3	5.4	6.2	5.9	5.6	6.7	4.7
% Top 100 School	26.1	22.6	22.8	26.0	24.9	23.7	25.1	22.2
Mean Graduation Year	1994	1998	1998	1995	1996	1997	1997	1996
% At COI$\geq$ 30 AMC	3.6	3.5	3.7	3.6	3.5	3.5	3.7	3.3
Mean Market Size	969	1,380	922	1,050	1,440	1,410	438	431

Note: This table presents the summary statistics for key physician characteristics, conditional on being observed in the Medicare Provider Catalog with non-missing data. 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. $MainSpecialty$ 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). $Top100School$ and $Top25School$ are indicators for whether the physician attended a medical school whose ranking is in the top 100 (or top 25) composite rank from Schnell and Currie (2018) or from US News Medical School Research Rankings in 2023. All means are computed for physicians present at the year of entry. 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.

Table A2: 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 are difficult to account for using the aggregated Medicare Part D prescriber-year data. FDA indications are pulled from the official drug label at approval year, obtained using the Drugs@FDA database.

Table A3: Physician Response to Detailing - Awareness
(Extended Sample)

	Namzaric	Corlanor	Glyxambi	Xultophy	Soliqua	Repatha	Praluent	Aristada
Panel A: Extensive Margin Response Given No Previous Prescription								
Detail	0.342***	0.021***	0.016***	0.020***	0.057***	0.031***	0.052***	0.073***
	(0.022)	(0.004)	(0.004)	(0.006)	(0.007)	(0.005)	(0.009)	(0.021)
N	659828	556709	671444	419896	415641	639176	638712	122041
Panel B: Differential Share Response by Awareness (Lagged Prescription Indicator)								
Detail	-1.332***	-0.036	-0.114***	0.010	0.034	-0.035***	-0.141***	-0.605*
	(0.356)	(0.022)	(0.030)	(0.047)	(0.036)	(0.011)	(0.031)	(0.324)
Interaction	15.597***	0.624***	1.908***	4.237***	2.321***	0.559***	0.690***	4.659***
	(0.363)	(0.048)	(0.135)	(0.502)	(0.150)	(0.024)	(0.035)	(0.387)
N	680551	558300	673089	420137	416179	642629	642629	122751

Note: This table replicates the findings of Table 3 for the extended sample. For more detailed notes, see Table 3.

Table A4: Differential Response by Experience and Beliefs (Extended Sample)

	Namzaric	Corlanor	Glyxambi	Xultophy	Soliqua	Repatha	Praluent	Aristada
Panel A: Experience (Lagged 365-Day Supply)								
Detail	18.776**	-0.348	-1.667***	-1.381	-1.037	-0.225	-0.618***	1.776
	(7.358)	(0.365)	(0.513)	(1.076)	(0.698)	(0.221)	(0.183)	(1.270)
Interaction	0.793**	0.241***	1.033***	0.973***	0.687***	0.226***	0.239***	0.567***
	(0.380)	(0.043)	(0.162)	(0.328)	(0.107)	(0.044)	(0.017)	(0.111)
N	20482	1585	1624	240	538	3384	3806	690
Panel B: Mean Beliefs (Lagged Benchmark Residual)								
Detail	1.536	0.843**	-0.602	0.983	0.181	-0.164	0.003	0.556
	(4.109)	(0.396)	(0.491)	(1.200)	(0.612)	(0.255)	(0.156)	(1.179)
Interaction	10.132***	1.182***	0.235	-0.031	0.194**	0.212***	0.303***	-0.113
	(1.528)	(0.445)	(0.155)	(0.546)	(0.097)	(0.050)	(0.031)	(0.325)
N	20482	1585	1624	240	538	3384	3806	690

Note: This table replicates the findings of Table 4 for the extended sample. For more detailed notes, see Table 4.

Table A5: Firm Detailing Behavior (Extended Sample)

	Namzaric	Corlanor	Glyxambi	Xultophy	Soliqua	Repatha	Praluent	Aristada
Lag Detail	0.280***	0.537***	0.458***	0.383***	0.416***	0.584***	0.395***	0.573***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.009)
Lag Experience	0.002***	0.045***	0.036***	-0.002	0.086***	0.033***	0.046***	0.017***
	(0.001)	(0.005)	(0.005)	(0.009)	(0.007)	(0.003)	(0.007)	(0.003)
Lag Belief	0.000	-0.001***	-0.002***	0.001**	0.000	-0.001	-0.002***	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)

Note: This table replicates the findings of Table 6 for the extended sample. For more detailed notes, see Table 6.

Table A6: Differential Response by Beliefs: Alternative Specifications

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Annual Expert Model								
Interaction	3.763***	1.710***	1.274***	1.871***	3.070***	6.916***	1.728***	3.003***
	(0.219)	(0.419)	(0.299)	(0.236)	(0.295)	(1.061)	(0.127)	(0.221)
Panel B: Flexible Interaction Specification								
Interaction|	2.966***	0.725***	4.476***	1.417***	2.514***	6.168***	1.370***	5.345***
$(Belief > 0)$	(0.165)	(0.178)	(1.165)	(0.160)	(0.245)	(1.158)	(0.098)	(0.285)
Interaction|	3.972***	1.978***	0.639	2.001***	1.756***	1.719**	-0.018	2.374*
$(Belief < 0)$	(0.206)	(0.233)	(0.702)	(0.330)	(0.157)	(0.715)	(0.322)	(1.442)

Note: This table presents the estimation results of prescription share 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 Section 4.1 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 baseline 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Physician Utility, Learning, and Prediction Derivations

In this appendix, we detail the physician prescription decision-making and learning process. We assume a risk-averse physician is uncertain about the quality of a drug for a given patient (or for a set of patients). They can learn about this quality from detailing visits and make prescribing decisions that maximize expected drug quality for a given patient (or for their patient mix) in each period. To highlight the role of information, we assume physician utility depends only on the expected quality of the drug in treating the given patient. While the model for a given drug is at the physician-patient-time level, we note that it is fairly straightforward to aggregate to the physician-time level to match that of our empirical data (Narayanan and Manchanda (2009)). Finally, we also note that the purpose of our model is to identify the informational effects specific to detailing, and as such abstract away from the within-patient learning of an 'experience good' presented in work on pharmaceutical demand under uncertainty (Crawford and Shum, 2005; Coscelli and Shum, 2004).

We model a risk-averse physician, i, who learns about the quality of drug, d, for a given patient, p, and makes prescribing decisions that maximize utility. We first present the utility and learning framework for a single patient, p, removing the drug subscript d for simplicity as the analysis is done separately for each drug. We then use this to show the mathematical derivations that are the basis for our model predictions in section 2.1.

Physician Utility

Let $\tilde{u}_{ip}$ be utility that physician i receives when prescribing the drug to the patient. We follow the literature and define utility as follows:

$$\tilde{u}_{ip} = U(\mu_p^*) \tag{B.1}$$

Here, μ_p^* is the true (unknown) quality of the drug in treating patient p. We define the outside option to be all other potential treatments and normalize its utility to 0. Thus, μ_p^* represents the quality relative to the alternatives.

The physician does not know the true drug quality but has distributional beliefs about its value. Specifically, physician i has a prior belief that the true quality of the drug for patient p follows a normal distribution with mean μ_{0ip} and variance σ_{0ip}^2: $\mu_p^* \sim N(\mu_{0ip}, \sigma_{0ip}^2)$. The physician learns about quality over time and updates beliefs in a Bayesian framework, described further below.

We model utility, U, as a constant absolute risk aversion utility function with risk aversion parameter ϕ. The certainty equivalent utility, u_{ip}, is derived as follows:

$$u_{ip} = U^{-1}\left(E[U(\mu_p^*)]\right) \tag{B.2}$$

$$u_{ip} = \frac{1}{\phi}\log\left(\int_{\mu^*} -\exp\left(-\phi\mu^*\right) dF(\mu^*)\right)$$

$$u_{ip} = \mu_{ip} - \frac{\phi}{2}\sigma_{ip}^2 \tag{B.3}$$

Learning about True Drug Quality: μ_p^*

Physician i starts with some prior belief about the quality of the drug, with mean μ_{0ip} and variance σ_{0ip}^2. The physician will learn over time via noisy signals of true drug quality. She will likely receive these signals from many sources (e.g., patient feedback, peers, medical journals, etc.), but given the focus of this paper, we only model learning from detailing visits and assume all other learning is exogenous.

Specifically, if physician i is detailed, she receives a noisy signal $\tilde{d}_p \sim N(\mu_p^*, \sigma_D^2)$. In other words, detailing visits can provide information about the quality of the drug for treated patients of type p. While detailing information must be accurate of true drug quality μ_p^* on average, the information can also be noisy, which is denoted by signal variance σ_D^2. With normally distributed prior beliefs and detailing signals, a Bayesian updating physician will

have the following posterior belief if detailed: $\mu_p^* \sim N(\mu_{ip}, \sigma_{ip}^2)$ where

$$\mu_{ip} = \frac{\sigma_D^2}{\sigma_D^2 + \sigma_{0ip}^2}\mu_{0ip} + \frac{\sigma_{0ip}^2}{\sigma_D^2 + \sigma_{0ip}^2}\tilde{d}_p \tag{B.4}$$

$$\sigma_{ip}^2 = \left(\frac{\sigma_{0ip}^2\sigma_D^2}{\sigma_{0ip}^2 + \sigma_D^2}\right) \tag{B.5}$$

This shows how expected beliefs about drug quality in treating a given patient is a function of whether or not they were detailed. Therefore, physician utility of prescribing the drug for a given patient is a function of detailing and we can re-write Equation (B.3) as follows:

$$u_{ip}(D_i) = \mu_{ip}(D_i) - \psi\sigma_{ip}^2(D_i) \tag{B.6}$$

where $D_i \in \{0, 1\}$ indicates detailing visit to physician i, $\psi = \frac{\phi}{2}$ denotes the risk-aversion term and

$$\mu_{ip}(D_i) = \begin{cases} \mu_{0ip} + \frac{\sigma_{0ip}^2}{\sigma_D^2 + \sigma_{0ip}^2}\left(\tilde{d}_p - \mu_{0ip}\right), & \text{if } D_i = 1 \\ \mu_{0ip}, & \text{otherwise} \end{cases} \tag{B.7}$$

$$\sigma_{ip}^2(D_i) = \begin{cases} \sigma_{0ip}^2\left(\frac{\sigma_D^2}{\sigma_{0ip}^2 + \sigma_D^2}\right), & \text{if } D_i = 1 \\ \sigma_{0ip}^2, & \text{otherwise} \end{cases} \tag{B.8}$$

Mapping to Model Predictions

In Section 2.1, we derived four main predictions about the role of information in physician response to detailing. The first prediction relates to the awareness channel and comes directly from the fact that a detail visit adds the drug to the physicians consideration set with certainty. In this appendix, we derive how the above model of physician utility and learning guides the remaining three model predictions, (ii) - (iv).

Recall, we define the effect of detailing on a given physician as the difference in the share of patients they prescribe if they were detailed less the share of patient they prescribe if they were not detailed. For simplicity in derivations, we show the effect of detailing on physician

utility for a given patient, i.e. $\Delta u_{ip} = u_{ip}(1) - u_{ip}(0)$. Plugging in utility from Equation (B.6), we have:

$$\begin{aligned}\Delta u_{ip} &= [\mu_{ip}(1) - \psi\sigma^2_{ip}(1)] - [\mu_{ip}(1) - \psi\sigma^2_{ip}(1)] \\ &= \underbrace{[\mu_{ip}(1) - \mu_{ip}(0)]}_{\text{Mean Belief Effect}} + \psi \underbrace{[\sigma^2_{ip}(0) - \sigma^2_{ip}(1)]}_{\text{Uncertainty Effect}}\end{aligned}$$

We can then input the prior and posterior mean beliefs and uncertainty from Equations (B.7) and (B.8) above, rearranging to give us:

$$\Delta u_{ip} = \left(\frac{\sigma^2_{0ip}}{\sigma^2_{0ip} + \sigma^2_D}\right) \times \left(\tilde{d}_p - \mu_{0ip} + \psi\sigma^2_{0ip}\right)$$

Using this equation, it is straightforward to show how the effect of detailing differs across physicians with different prior mean beliefs and prior uncertainty.

First, the effect of detailing is decreasing in physician prior mean beliefs about the drug as $\frac{\partial \Delta u_{ip}}{\partial \mu_{0ip}} = -\left(\frac{\sigma^2_{0ip}}{\sigma^2_{0ip}+\sigma^2_D}\right) < 0$. This gives us prediction (iii) Physicians with higher mean beliefs (more optimistic about drug quality) will respond less to detailing visits relative to those with lower mean beliefs about drug quality.

Second, the effect of detailing is increasing in physician prior uncertainty about the drug. The derivative of the detailing effect with respect to prior uncertainty is given by:

$$\frac{\partial \Delta u_{ip}}{\partial \sigma^2_{0ip}} = \left(\frac{\sigma^2_D}{(\sigma^2_{0ip} + \sigma^2_D)^2}\right) \times \left(\tilde{d}_p - \mu_{0ip} + \psi\sigma^2_{0ip}\right) + \psi\left(\frac{\sigma^2_{0ip}}{\sigma^2_{0ip} + \sigma^2_D}\right) \tag{B.9}$$

This derivative is positive as long as $\tilde{d}_p \geq \mu_{0ip} - \psi\sigma^2_{0ip}\left(1 + \frac{\sigma^2_D}{(\sigma^2_{0ip}+\sigma^2_D)}\right)$. Intuitively, the effect of detailing is increasing in prior uncertainty unless a physician receives a very negative signal relative to their prior and has very certain beliefs. However, the effectiveness of an

informative detailing campaign requires that physicians have generally low and uncertain prior beliefs about a drug's quality. Thus, under a model of informative detailing, this condition is rarely violated, and we maintain the prediction that responses to detailing will be increasing in prior uncertainty. In other words, this gives us prediction (ii) Physicians with less uncertain beliefs will respond less to detailing visits relative to those with more uncertain believes.