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

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April 17, 2026

Abstract

This paper theoretically and empirically examines the role of information in 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 learn about drug quality and prescribe accordingly. We derive several predictions about the role of information in these visits, which we then test empirically using prescriptions and pharmaceutical detailing visit data. We find limited empirical support of learning as the dominant mechanism, though cannot rule it out completely. We conclude with discussing alternative models that may be more consistent with the observed empirical patterns.

JEL Classification: I1, D8, L1, M3

*We would like to thank Abby Alpert, Elena Falcettoni, Juan Pantano, Rubaiyat Alam, Sung Jae Jun, Zach Brown, and seminar/conference participants for valuable comments and suggestions. We also thank Sheikh Atiya Islam, Aryan Safi, Bea Rivera, and Cameron Deal for excellent research assistance. The views here do not represent those of the Federal Reserve Bank of Chicago or the Federal Reserve System. All errors are our own.

1 Introduction

Pharmaceutical firms often promote drugs through "detailing," wherein drug representatives meet directly with physicians. One common form of detailing involves a small in-kind payment to the physician, typically via 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., 2025). While proponents argue that this marketing practice provides valuable information (Hincapie et al., 2021), there is limited evidence on the extent to which it is motivated by information provision rather than other aspects of traditional advertising, such as brand loyalty, reputation, or prestige, which can be 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—based on the number of in-kind meal payments to physicians recorded in the Centers for Medicare & Medicaid Services (CMS) OpenPayments database—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 are most consistent with alternative models, such as traditional preference-based advertising.

In the information-based 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 have relatively low mean beliefs about a drug's quality will have greater increases in their prescriptions. Finally, repeated detailing 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 whether these predictions are supported empirically, we combine data on the universe of pharmaceutical detailing visits, compiled in the CMS OpenPayments database, with physician-year level panel data on Medicare Part D prescriptions and patient characteristics from 2014 to 2019. Throughout the paper, we use "detailing" visits to refer to the common in-person interactions between pharmaceutical firms and physicians that involve in-kind payments via meals. These interactions are recorded in the OpenPayments database following a federal mandate in 2013.

We focus on new drugs released between 2014 and 2017 with large detailing campaigns and clear indications for an observable chronic condition in the public Medicare data. There are eight drugs that meet these criteria: three for chronic obstructive pulmonary disease (COPD), three for diabetes, one for mental illness, and one for 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., 2025).

While we cannot directly observe information exchange or physician beliefs, we use empirical measures to examine whether the data are broadly consistent with the model's predictions. First, we test whether the effect of detailing is greater among physicians without a prior prescription history with the drug (and thus potentially unaware). We find that such physicians have significant responses on the extensive margin. However, physicians with a previous prescription history have greater responses to detailing in their prescription share than otherwise similar physicians without previous prescriptions. While the extensive margin responses are consistent with the model's predictions of information via awareness, the differences in prescription share responses depart from what a pure learning model would predict and may reflect other forces operating in detailing.

Next, we test whether physicians with less uncertainty about (more experience with) the drug and/or higher beliefs about drug quality have lesser responses to detailing as the information-based model would predict. We measure physician experience using their volume of Part D prescriptions of a particular drug 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, defined as the patient-adjusted prescription share among "expert" physicians. Across all drugs in the sample, we find that more experienced physicians and physicians with relatively high prescription shares have greater responses to detailing, all else equal. Both patterns run counter to the learning model predictions, suggesting that other kinds of advertising effects may influence physician responses to detailing.

Finally, we examine 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, mean beliefs, whether they were detailed in the prior year, and a set of controls for specialty, patient volume, and patient characteristics. We find that firm detailing behavior is unlikely to align with pure information-based targeting. Instead, firms appear to favor revisiting previously detailed physicians rather than distributing potentially new information to new doctors. Across all drugs in the sample, firms are more likely to target physicians who have more experience with the drug. For five out of eight drugs, firms are more likely to detail physicians with relatively high prescription share and only appear to target relatively low prescribers for one or two of the drugs.

Our empirical results on physician responses to and firm targeting of detail visits are mutually consistent, and both sets of results suggest that learning and information are unlikely to be the primary mechanism. Compared to otherwise similar physicians, our results suggest that 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. We show these results are broadly robust by conducting additional tests that rely on alternative specifications, market definitions, or various physician/drug subsamples. Although we cannot provide definitive causal identification of specific mechanisms, we interpret systematic empirical deviations from the model's predictions as suggestive evidence that the data are not generated by a pure information-based learning model. 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, noting that the empirical patterns align more closely 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 generally, mostly focused on demand-side responses. More specifically, there is a growing literature that studies advertising directly to physicians, i.e. pharmaceutical detailing. 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).[1] 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. Shapiro (2018) finds that detailing visits likely informed physicians about positive antipsychotic side effect profiles.

[1] 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., 2025), the latter of which motivates the approach we use in this paper.

Huang et al. (2019) show that detailing visits reduce statin 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.

From a modeling perspective, we draw on the literature studying 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 structural models of physician 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). We complement this literature by taking an alternative empirical approach. Rather than estimating a structural model of physician learning, we derive comparative statics from a standard model of information provision and test whether various patterns observed in aggregate data are consistent with the learning-based model predictions. In this sense, our contribution is not to quantify physician learning, but to evaluate whether information provision is the primary mechanism behind meal-based detailing.

Further, we study multiple new drug launches across several drug classes. The novelty of the drugs provides a setting where information should play a large role relative to more established drugs and allows us to study detailing campaigns at their height. By comparing drugs across several classes, we show that data patterns are consistent across drug types and broadly differ from what would be expected under a standard model of learning. Some of our findings contrast with settings where information plays a more dominant role. For example, Ching and Ishihara (2012) find that detailing by multiple brands for the same molecule has larger effects on molecule-level prescriptions (information) than on brand-specific prescriptions (persuasion) in the context of diuretic drugs in Canada. We note that differences in results across studies may reflect variation in empirical settings: e.g., the degree of within-molecule competition, the scope of detailing activities examined, and the types of prescribing outcomes observed.

Finally, our study 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 that detailing efforts for Chantix, a smoking cessation drug, increased after FDA removal of the black-box warning, likely to disseminate the positive information shock to physicians. Grennan et al. (2025) 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 relatively high-prescribing physicians, even with similar market size and case-mix, a pattern that differs from what an information-based response model would predict.

2 Setting & Theoretical Framework

In the United States, advertising to physicians is an integral part of prescription drug marketing strategies, taking the form of honoraria for speaking engagements, sponsored conferences, free drug samples, or the focus of this paper, detailing visits. These visits typically occur over a meal in which a drug manufacturer's representative 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.[2]

Firms use information on physician prescription behavior and patient-mix demographics to organize and target their detailing campaigns (Fugh-Berman and Ahari, 2007). Repre-

[2]Meal-based detailing visits represent the advertising channel reaching the most physicians by far. The next largest category by reach, travel and lodging, covered only 630 thousand physicians in 2019.

sentatives are assigned a territory and a ranking of physicians based on market size and past prescribing history. They use this information to decide who to visit, and their compensation (via bonuses) is often tied to prescription-based goals, giving them an incentive to prioritize physicians where they expect the greatest effect on total prescriptions.

Representatives focus on a single drug or small group of drugs for a given condition and are prepared by firms with specific content to deliver across all visits. 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.[3] If physicians need information beyond the drug representative's purview, they're directed to other avenues (e.g., direct communication with pharmaceutical company experts likely outside of the marketing department).

This pharmaceutical marketing practice 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 improved transparency on the relationships between pharmaceutical firms and physicians via mandatory public reporting of detailing interactions, which is where the data for this paper originates.

Before moving to the empirical analysis, we first introduce a stylized model of physicians and firms in which detailing affects prescription behavior only through information and learning. The purpose of this model is to generate transparent comparative statics for a standard learning model. In the model, physicians write prescriptions to maximize expected drug quality for a given patient. Detailing visits provide information about the

[3]See PhRMA Code on Interactions with Health Care Professionals, `https://www.phrma.org`, accessed April 18, 2025.

drug, updating physicians' consideration sets and quality beliefs. 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 compare to empirical patterns in the data. Appendix B provides additional model details and derivations of model predictions.

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. 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 the 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. 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 ($D_i = 1$), the utility from prescribing is influenced through the effect detailing has on the physician's beliefs about drug quality for a given patient, p. Here, $\mu_{ip}(1)$ captures the effect of a detailing visit on the physician's average belief of drug quality and $\sigma^2_{ip}(1)$ captures the effect on the physician's uncertainty about drug quality.

In addition to beliefs about the quality 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 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 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 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

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.[4]

Beliefs about Drug Quality: The beliefs information channel occurs through the information about drug quality 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 ($D_i = 0$), they do not update their beliefs. If they are detailed ($D_i = 1$), 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 $\tilde{D}_p \sim N(\mu^*_p, \sigma^2_D)$.[5] The physicians update their beliefs according to Bayes rule. Their posterior mean and variance of drug quality, as a function of detailing, is given by the following:

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

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

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

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

[5]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.

ing 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 with relatively low prior mean beliefs about drug quality (low μ_{0ip}) will have greater positive response to detailing visits compared to physicians with relatively high prior mean beliefs (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 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 constant profit π,[6] and the cost

[6] There are reasons why π might not be constant, but as long as profit depends on total

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 with greater expected prescription behavior response, i.e. those with larger ΔS_i.

Firms may face more complex costs, but for many cost functions, detailed physicians would have greater predicted response than every non-detailed physician. Given that detailing costs may vary across physicians due to local traveling or transportation costs, we note that predictions derived from the model apply across physicians *within* the same geographic area, which we account for in our empirical exercise through county or zip-code fixed effects.

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 de-

prescriptions rather than a given physician's prescription, the predictions from this section are robust.

tail. 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.

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 monetary and in-kind payments from drug manufacturers to physicians, federally mandated in 2013 and maintained by CMS. The data contain the date of the visit, the nature of the payment (e.g. a purchased meal), the monetary value of the payment, the names of up to five products 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 as detailing visits.

Using this data source, we construct a physician-year panel with information on detailing visits by drug from January 2014 to December 2019. We define D_{idt} as an indicator for whether physician i received a detailing visit for drug d 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.[7]

An important caveat is that advertising to physicians is broader than the in-kind meal transfers we study. The OpenPayments database contains information on other kinds of transfers (e.g. travel, grants, and consulting), but these are rare relative to meals. There are also important advertising activities that are not recorded in the data, such as providing samples, brochures, or co-pay coupons, which may occur with or without a recorded meal in the data. Thus, "detailing visits" in this paper capture the documented meal itself and the other detailing/informational context that accompanies them.

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 specialty, 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 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.[8] For each drug, d, we compute a physician-year specific prescription share ($RxShare_{idt}$)

[7]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. 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.

[8]We use medical school rankings from Schnell and Currie (2018) and 2023 US News rankings. See Appendix Table A1 for summary statistics of physician characteristics, by

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.[9]

We match the prescription data to the OpenPayments data using a physician-level mapping to NPI provided by CMS.[10] This results in a physician-year panel with both detailing visits and prescription claims by drug, in addition to patient-mix and physician characteristics.

AMSA Scorecards

The American Medical Student Association (AMSA) collects information on conflict of interest (COI) policies for member academic medical centers (AMC). The AMSA gives each center a score in a range of fields governing different aspects of COI policies (see Appendix Figure A1 for an example scorecard). The scores range from 1 to 3, with 3 being the most restrictive with respect to potential conflicts. We follow Grennan et al. (2025) in creating a summary measure for each AMC-year by summing the score across all 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.

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drug.

[9]The denominator is constructed using the total number of beneficiaries seen by the physician in a given year, multiplied by the observed share of beneficiaries diagnosed with the relevant chronic condition.

[10]The data do not have complete coverage of NPI in the earlier sample years. To fill the gaps, we sequentially match unmatched physicians on name, name and state, name and city, and name and zipcode. We keep only physicians that are uniquely identified in each data set by the match criteria. We identify the NPI for 99.8% of the total number of payments.

3.2 Sample Selection

We study detailing campaigns of branded drugs that enter the market between 2014 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.

Next, we remove eight drugs that are specialized to unobservable subsets of the patients with the particular chronic illness to reduce measurement error in the share of patients to which the drug is prescribed. For instance, we remove Corlanor, used to treat those with chronic heart failure (CHF), as it requires specific ranges for cardiac function metrics and vitals which are unobservable in the aggregated Medicare Part D data. See Appendix Table A2 for the more specialized drugs that we exclude from the main analysis.

For the remaining eight in-sample drug, we select a sample of relevant prescribing physicians. 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] We restrict the sample to physicians that live within 300 kilometers of an AMC.[12] Table 1 provides information on the sample drugs and summary statistics on prescriptions and detailing for each drug.

[Table 1 here.]

3.3 Motivating Data Patterns

In this section we present three data patterns that motivate the analysis that follows. First, the prescription share of a particular drug is greater and increases faster among physicians

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

[12]This restriction ensures variation in the instrument (distance to an AMC) has a plausible effect on the propensity to be detailed.

that receive detailing visits from the manufacturer, even after adjusting for differences in patient-mix across physicians. Figure 1a shows the average prescription share for all drugs in the sample, separate for 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 patient mix-adjusted prescription share among ever detailed physicians is more than double that of physicians that never receive a detailing visit.

Second, manufacturing firms tend to repeatedly detail the same set of physicians rather than reach as many physicians as possible. In Figure 1b, 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 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 1).

[Figure 1 here.]

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 2a, we group AMC physicians by the conflict of interest score assigned to the AMC in which they practice. 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 who do.

Importantly, we note that there are likely 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 drug detailing representatives find it less worthwhile to travel to an area where the main hospital is excluded. In Figure 2b, we show that the probability of being detailed increases with the distance between a physician's practice location and the closest AMC 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, conditional on patient-mix, specialty, and year/area controls.

[Figure 2 here.]

4 Empirical Tests for Information

In this section, we use the empirical 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. We first define empirical analogs of these information channels, then present empirical specifications and results for physician response predictions, followed by those for the firm.

4.1 Measures of Awareness, Uncertainty, and Mean Beliefs

The three information channels described in the theoretical model are awareness, uncertainty, and mean beliefs. Because these objects are not directly observed, we rely on proxies constructed from prior prescribing behavior. The model's predictions concern the differential response to detailing, comparing physicians with different levels of each information channel. Therefore, we construct empirical measures that serve as analogs to the model's concepts of information among otherwise similar physicians. In the empirical exercise, we control for observable differences using physician characteristics, patient-mix characteristics, and time/area controls. However, we recognize that residual unobserved heterogeneity may remain. We discuss this possibility and conduct robustness exercises that help assess the sensitivity of the results to this assumption in Section 5.

<u>Awareness:</u> Awareness of a drug d is defined by a physicians' consideration set (see Section

2.1). 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 a physician must be aware of the drug if they prescribed the drug in the past. In our empirical tests of the model's predictions, we ask whether there is an extensive margin response among those without a history of prescribing the drug within Medicare Part D, and whether those with a previous prescription history respond relatively less to detailing visits, all else equal. We note that the extent to which those who did not prescribe the drug in the past (or prescribed outside of Medicare Part D) 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.

Uncertainty: We define physician prior uncertainty (σ^2_{0ip} from Section 2.1) as inversely related to the physician's previous experience, i.e. physicians with more experience prescribing the drug have less uncertainty about the drugs' quality. We measure physician experience using lagged prescription volume measured in 365-day supply. In other words, we assume that, compared to otherwise similar physicians, those with more experience prescribing the drug—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 are more uncertain. In our empirical test of the model's predictions, we ask whether physicians with higher prescription volume in the prior year respond relatively less to detailing visits, all else equal, and whether they are less likely to be detailed by the firm.

Mean Beliefs: Finally, we use an expert benchmark model approach to measure physician mean prior beliefs about drug quality. 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 (see Section 2.1). Our goal with the benchmark model is to measure where a physician's mean beliefs fall relative to the true drug quality and then test whether physicians with relatively higher mean beliefs about the drug quality, according to our measure, 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 share. We define expert physicians as those who work at an academic medical center with a high conflict of interest score, have prescribed the drug in the past, and focus on the prescriptions in the last year of the sample, $t = 2019$.[13] Assuming these expert physicians prescribe with full information and that X_{it} captures relevant variation in their patient mix, we can use their observed prescription share as a measure of true drug quality for a given patient-mix. We estimate a Probit model using data from these expert physicians, where X'_{it} includes an indicator for the main prescribing specialty and a vector of patient characteristics further described in the following section.

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

In the second step, we apply this benchmark model to all physicians in the sample to determine what a physicians' prescription share would be if they had behaved similar to the experts with the same patient mix and main specialty controls, X_{it}: $\widehat{RxShare}_{idt} = \Phi(X'_{it}\hat{\kappa})$.

In the 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 is a proxy for 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 relatively higher mean beliefs about the quality of the drug. Conversely, if the residual is negative, the physician is prescribing *less* and therefore may have relatively low mean beliefs. In our empirical test of the model's predictions, we ask whether physicians with higher mean beliefs about drug quality (higher benchmark residual in the prior year) respond relatively less to detailing visits, all else equal, and whether they are less likely to be detailed by the firm.

[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 5 and Appendix C.

4.2 Physician Response to Detailing

4.2.1 Empirical Specifications

In our analysis of physician behavior, we 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 physicians 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 previous prescriptions, we estimate the latter 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 equations, $D_{idt} \in \{0, 1\}$ 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.

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, indicators for the specialty of physician i (e.g. pulmonologist or internal medicine),[14] and patient-mix composition controls. These patient-mix controls include the average age, the average risk score, fraction of patients that are male, white, and dual-eligible

[14] About 2.5% of observations are dropped due to missing physician characteristics. Results are consistent with an alternative specification that keeps the full physician sample and excludes physician characteristic controls.

for Medicaid, and the fraction of patients diagnosed with each of the following chronic conditions: chronic 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 a physicians' relevant market size. We also include the 9-category urban/rural continuum codes, market size, physician peer network size,[15] and year fixed effects, λ_{dt}. Each regression is estimated separately for each drug d, and standard errors are clustered at the physician practice zip code level.

Detailing visits may be correlated with unobserved determinants of prescribing, such as patient appropriateness or anticipated responsiveness, not captured by our controls. We address this concern using an instrumental variable strategy based on proximity to academic medical centers with high conflict-of-interest scores. Specifically, 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 detail visit propensity (Grennan et al., 2025).[16] 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 2). 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.[17] We bin

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

[16]Grennan et al. (2025) use a different aggregation of the same underlying source. The instrument is a detail propensity based on the weighted AMSA conflict of interest score in the physicians' hospital referral region (excluding scores at their own hospital service area and hospital).

[17]In addition to the standard linear IV, we have also estimated many of the results that

distance in 5 kilometer increments up to 50 kilometers from an AMC, and 25 kilometer increments up to 300 kilometers 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.[18] In the empirical tests of differential effects by prior information (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.

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. 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.

Figure 3 visualizes the point estimates and standard errors for each estimation (corresponding tabular results in Appendix Table A3), where Panel A corresponds to the extensive margin test (Equation (9)) and Panel B to the differential effect of detailing by previous prescription history (Equation (10)).

[Figure 3 here.]

Figure 3a 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

follow using a control function approach and marginal treatment effects, and we arrive at qualitatively similar findings.

[18]We choose the bin size to scale with how quickly the detailing probability changes with distance (see Figure 2b). The exact specification of the bin size has little quantitative effect on the results.

for all but one. For most drugs, 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 3b 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. That is, physicians who have previously prescribed the drug increase prescribing *more* in response to a detailing visit than observably similar physicians that have not prescribed the drug before.

While the extensive margin results 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 A3). 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 test 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 in response to detailing than otherwise similar physicians with less experience. And, physicians with higher mean prior beliefs about the drug's quality should increase their prescriptions less than those with lower prior beliefs.

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 Figure 4 and corresponding Appendix Table A4.

[Figure 4 here.]

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. However, 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, all else equal.

Response over Time

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

We 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 Figure 5 and corresponding Appendix Table A5.

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

We find detailing effects do not fall over time. In nearly every case, the response to detailing increases with each year following entry.

[Figure 5 here.]

When taken altogether, we interpret the findings of this section to be suggestive evidence that information is unlikely to be the key mechanism driving the positive prescription 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 advertising effects, such as prestige or brand loyalty, may be driving physician responses. We assess the robustness of these results in Section 5 and discuss alternative models in Section 6.

4.3 Firm Detail Visit Targeting

4.3.1 Empirical Specifications

In Section 2.2, we present a model in which profit maximizing firms target detailing visits to physicians with the highest expected prescription 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 firm's 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 among otherwise similar physicians, firms will target those 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:

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

We assess whether a physician i is less likely to be 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 ($\text{Experience}_{id,t-1}$), and if they had high beliefs about drug quality (i.e., high-prescribing relative to his/her patient-mix-adjusted benchmark level) in the previous year ($\text{Belief}_{id,t-1}$).

We control for the number of patients with the relevant chronic illness seen by the physician, N_{idt}, which is an important factor in the potential total prescription response from a detailing visit. We use $f(N) = N + \sqrt{N}$ 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, including the binned distance to high conflict-of-interest AMCs (detailed in Section 4.2). In addition, we include county fixed effects to account for possible regional variation in detailing costs. We also 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. As in Section 4.2, we control for a measure of the number of peer physicians, which Agha and Zeltzer (2022) find is a factor in the detail targeting decision. Finally, Λ_{dt} are year fixed effects. We estimate the model for each drug separately, and cluster standard errors at the physician practice zip code 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 Figure 6 and corresponding Appendix Table A6. Note that while displayed in different figure panels, all coefficients relating to a particular drug come from the same regression. In Section 2.2, we show that each of these coefficients should be negative if information is the dominant mechanism. However, the coefficients we estimate are positive and significant in nearly every specification and for nearly every drug in the sample. Taken together, these patterns provide little support for the information-based model's predictions and point in the opposite direction.

[Figure 6 here.]

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 45 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 who have higher prior experience with the drug, all else equal. Finally, for a majority of the drugs, firms are more likely to target physicians that prescribe more of the drug relative to their predicted benchmark. We note there are two firm-drug pairs that appear to target relatively low-prescribers, Basaglar and Tymlos, though the former is only marginally significant at the 10% level.

Next, we test whether firm targeting policies 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 Equation (12) but allow the parameters for previous detailing, experience, and beliefs to vary by year following entry.

We find that for three out of eight drugs, firms are more likely to target relatively low-prescribers in the first or 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, the first year following entry is when we see the strongest association between detailing and lagged detail visits and between detailing and lagged prescription volume. See Appendix Table A7 for the full set of results.

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 target physicians who exhibit the largest prescription responses to detailing. While firm targeting behavior cannot by itself identify whether physicians learn from detailing, it provides evidence on which physicians the pharmaceutical firms believe will respond to detailing with increased prescriptions. The targeting policies we estimate are suggestive evidence that information provision is unlikely to be the primary mechanism driving the prescription response to detailing visits. Taken together, the firm targeting patterns and physician response evidence are difficult to reconcile with predictions from the standard information-based model, and instead suggest a larger role for other advertising channels, which we discuss further in Section 6.

5 Robustness and Heterogeneity

It is important for the interpretation of these results that the data patterns we illustrate are general, rather than being driven by the specifics of our baseline specification. In this section, we summarize our main robustness checks; full details and results are provided in Appendix C. Broadly, we address two main threats to interpretation.

First, our controls may not fully account for unobserved heterogeneity in patient-mix appropriateness. In Appendix C.1, we assess the robustness of our results to additional unobserved heterogeneity in physician patient mix with two complementary approaches: (1) a discussion of OLS bias and comparison to IV estimates, and (2) redefining prescription share as the fraction of prescriptions within a narrow class of pharmacological substitutes rather than among all patients with the relevant chronic condition. The OLS vs IV comparison shows a downward OLS bias, suggesting that unobserved heterogeneity in patient mix is unlikely to be the dominant source of bias. This is supported by the finding that results using the redefined prescription share are qualitatively similar to the baseline results.

Second, in Appendix C.2 we consider the possibility that the data patterns reflect differences in the response to detailing across physicians unrelated to their drug-specific experience or beliefs. For example, a specialist physician may prescribe more of the drug and also learn more from detailing visits. Even with physician specialty fixed effects, this could distort the relationship between experience and detailing effects, without necessarily being inconsistent with a model of learning. To address this possibility and other sources of heterogeneity, we next assess the robustness of our results to alternative physician samples, drug samples, and empirical specifications.

We consider four alternative physician samples: physicians that ever accept any detail visit, physicians in the main prescribing specialty, physicians outside the main specialty, and a single cross-section from the second year following drug entry to address the fact that the awareness indicator is an absorbing-state. We also consider a zip code fixed effect specification replacing county-level fixed effects in the firm equation. Across all specifications, results are qualitatively similar to the baseline. We additionally check whether rising detailing responses over time reflect new drug information via label changes, test alternative benchmark model specifications, and replicate all main results on the extended drug sample. For full details and additional discussion of the robustness checks results, see Appendix C.

6 Advertising without Information

We have now presented a set of empirical patterns that are difficult to reconcile with the predictions of the stylized model of information presented in Section 2. The estimates of firm targeting policies align with the estimates of physician responses: firms target those with the greatest prescription response to detailing. However, these physicians with the greatest responses are unlikely to be the physicians that would benefit most from learning and information.

This naturally raises the question: what classes of models *are* consistent with the reduced-form patterns we document? In this section, we argue that a simple model of direct advertising effects (without information) provides a parsimonious way to rationalize many of the observed data patterns. We discuss alternative models of learning in Appendix D.

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 product descriptions. This explains why widely known product with relatively consistent characteristics still advertise. 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 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 enforce conflict of interest policies that limit the ability of affiliated physicians to accept detailing visits (see Figure 2). 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. For example, Ford truck owners like to see Ford advertisements, which make them feel even happier about their decision to own one. Analogously, notice that physicians receive the warm-glow effect from advertising for each prescription 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 suggestive of such a mechanism. Physicians with more experience and high-prescribers relative to their peers have greater prescription responses from being detailed (see Figure 4). Pharmaceutical firms know this and target high-prescribing physicians (see Figure 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 in this model 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 Appendix D, 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. We also discuss alternate models of learning (e.g., costly signaling models or heterogeneous learning rates). 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 provides a parsimonious way to rationalize many of the observed data patterns.

7 Conclusion

Detailing is a common practice used by pharmaceutical firms to market directly to physicians. In this paper, we focus on one pervasive form of detailing, specifically visits in which meals are provided by pharmaceutical firms to physicians. While previous research has shown that these visits generate additional prescriptions, less is known about the overall welfare implications of this practice. One way detailing visits can be welfare improving is through information provision, in which drug representatives inform physicians about drug quality and existence, enabling better prescribing decisions for their patients. We present a model that formalizes this information mechanism and generates a set of empirical predictions. We then use data from eight prominent drug entrants between 2014 and 2017 to examine whether observed prescribing and targeting patterns are consistent with these predictions.

In line with other findings in the literature, we find that meal-based detailing visits lead to greater prescription rates for nearly every drug in the sample. While we find some evidence that detailing visits may increase awareness of the drug, we also show that response to detailing is greater among physicians with more experience and among those whose prescription shares imply relatively high beliefs about true drug quality. These results suggest that while learning may play some role in the physician response, it is unlikely to be the dominant mechanism.

Further, the model 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. Holding all else equal, 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 prescribing more relative to their predicted benchmark rate (already have high mean beliefs about drug quality). In the data, however, we find the opposite. Firms are more likely to revisit previously detailed physicians, to target more experienced prescribers, and—–for several drugs—–to detail physicians with relatively higher prescribing rates compared to a measured benchmark. These patterns differ from the predictions of an information-based targeting model, and the targeting policies suggest that firms are more interested in detailing physicians who show a willingness to prescribe the drug, and detail them repeatedly.

Our model framework provides a useful perspective on pharmaceutical detailing by clarifying the predictions that arise when information exchange and learning drive physician responses and firm targeting. Across multiple tests, the empirical patterns we document differ from several key implications of this information-based model, providing evidence that physician learning from information exchange is unlikely to be a driving mechanism of pharmaceutical detailing. Our findings suggest that detailing practices may be primarily about traditional marketing incentives—brand reputation or prestige.

We note some important limitations. First, we focus on meal-based payments, which is just one form of detailing. It is possible that other forms of pharmaceutical detailing (e.g., webinars, conferences, or material distribution) carry greater informational content than the practice we study here. Second, we do not have data on the distribution of free samples or copay discounts, which could drive some of the estimated detailing effect. Because the drugs we study treat chronic illnesses, free samples are unlikely to represent a significant share of total treatment cost (which is why they are offered to begin with), and thus we view this mechanism as another potential wedge between physician decision making and the optimal allocation of drugs across patients. Finally, 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 research that directly investigates how the relationship between detailing and health outcomes maps back to patient welfare is an important area of future research.

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Table 1: Drugs and Summary Statistics

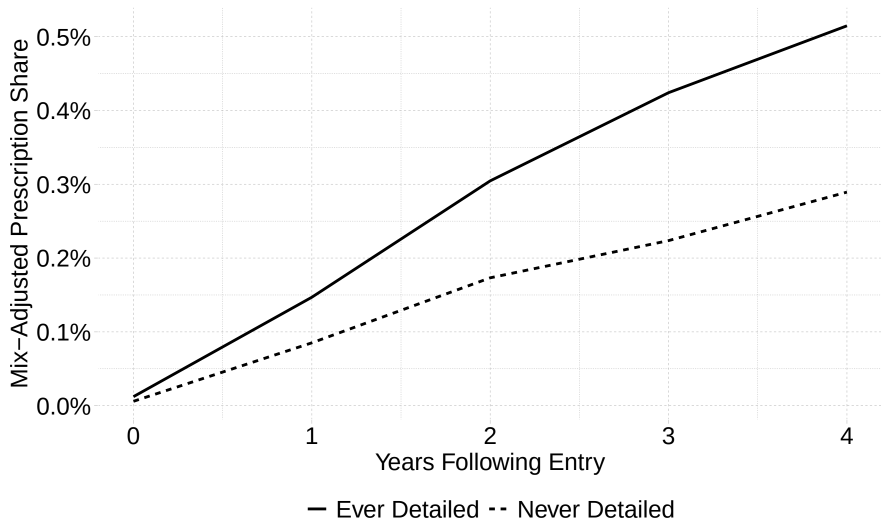
Drug Name†	Chronic Condition	Entry Year	Manufacturer	Scripts (thous.)	Ever Prescribe	Rx Share| Prescribe	Detail Visits (thous.)	Ever Detailed	Ever Prescribe| Detailed
Anoro	COPD	2014	GlaxoSmith-Kline	3135	0.18	0.015	447	0.14	0.55
Stiolto	COPD	2015	Boehringer Ingelheim	734	0.05	0.009	218	0.09	0.27
Bevespi	COPD	2017	AstraZeneca	137	0.02	0.008	193	0.06	0.12
Toujeo	Diabetes	2015	Sanofi	1980	0.15	0.011	358	0.14	0.50
Tresiba	Diabetes	2016	Novo Nordisk	1988	0.14	0.014	541	0.16	0.44
Basaglar	Diabetes	2017	Eli Lilly	1400	0.18	0.012	164	0.11	0.37
Tymlos	Osteoporosis	2017	Radius Health	36	0.01	0.009	31	0.03	0.13
Vraylar	Schizophrenia‡	2016	AbbVie	141	0.05	0.023	83	0.08	0.31

Note: This table displays the 8 drugs in the main estimation sample described in Section 3. For each drug, we list the condition it treats, the entry year, i.e. the first year the drug could be prescribed to patients, and the manufacturing firm. The remaining columns show summary statistics for each drug and the corresponding sample of physicians: the total number of prescriptions across the sample 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 ever detailed, and the share of physicians that ever prescribe the drug among those who were ever detailed.

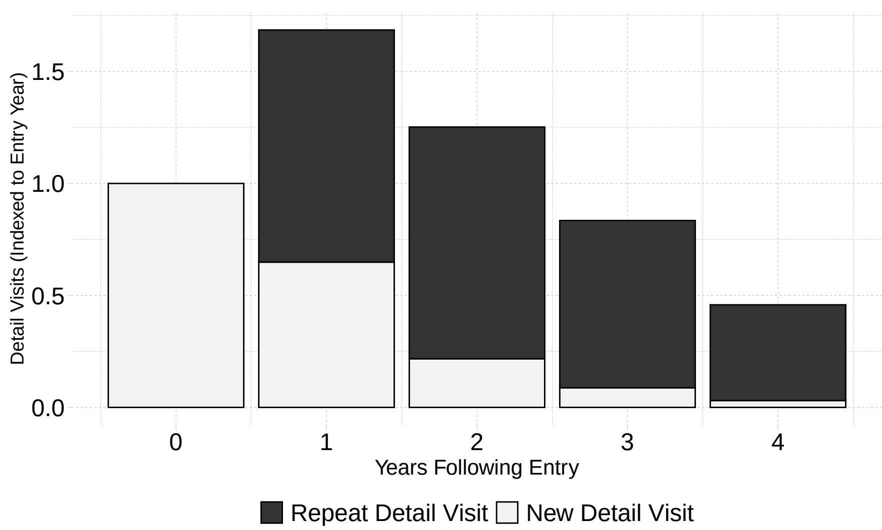
†: Drug names are shorted for the COPD drugs. Full names are, respectively: Anoro Ellipta, Stiolto Respimat, and Bevespi Aerosphere.

‡: Vraylar treats other mental health conditions as well such as bipolar I disorder.

Figure 1: Detailing and Prescription Patterns



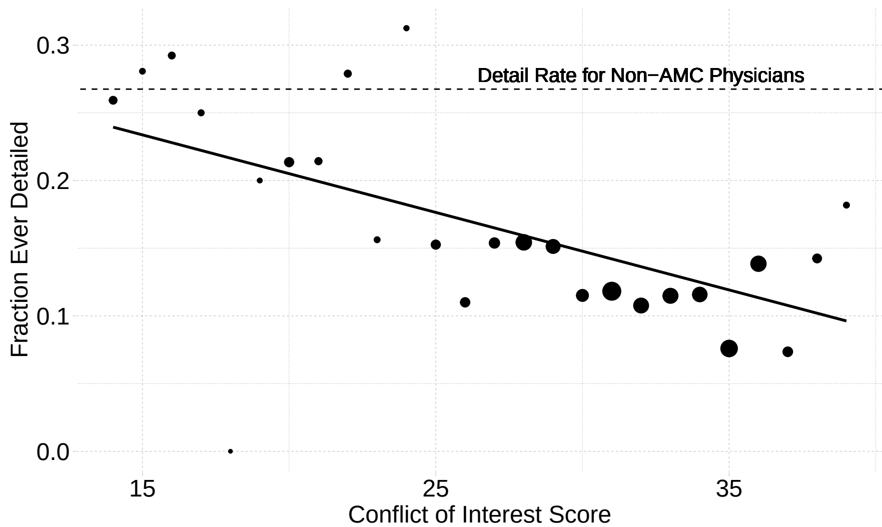
(a) Mix-Adjusted Prescription Share by Detailed



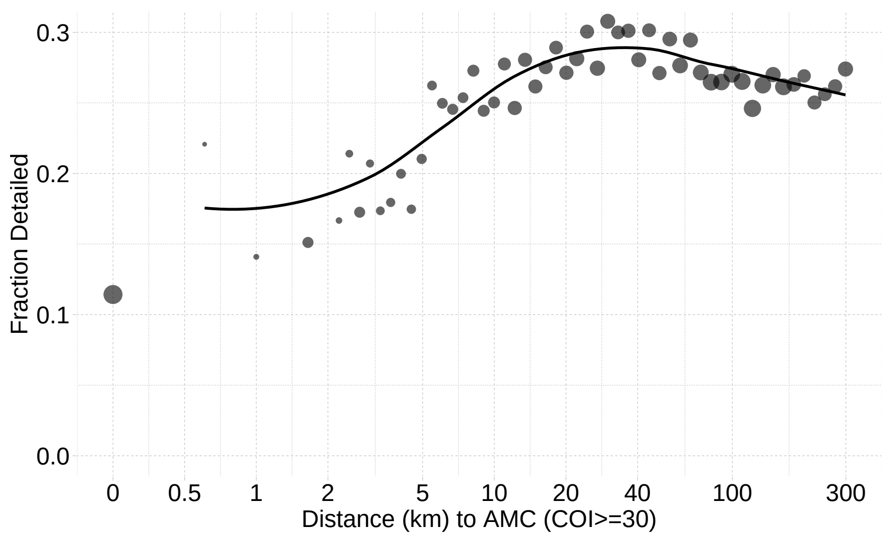
(b) Repeat Detail Visits by Year

Note: Panel (a) 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. Physicians that ever receive a detailing visit prescribe more of the target drug, and the prescriptions increase faster following entry. Panel (b) 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). Detail visits ramp up following the entry of the target drug and are primarily targeted towards the same set of physicians.

Figure 2: Detailing and COI at AMCs



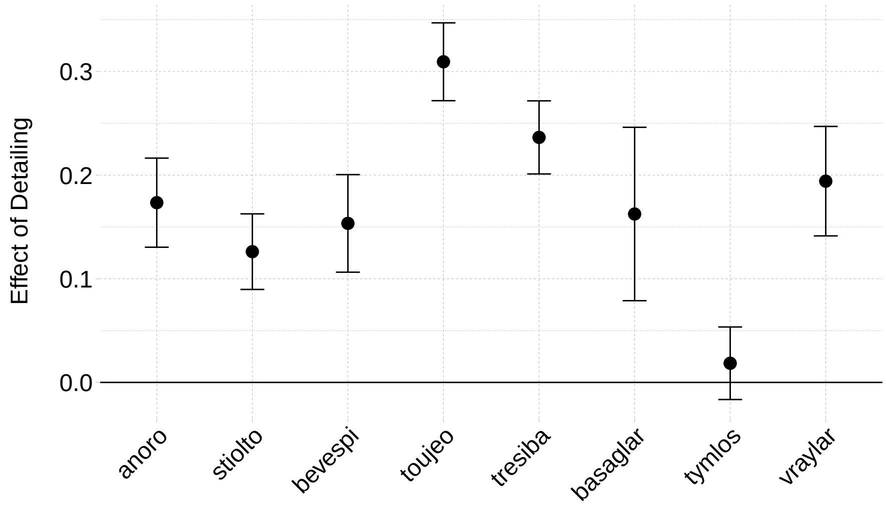
(a) Detail Propensity by AMC COI Score



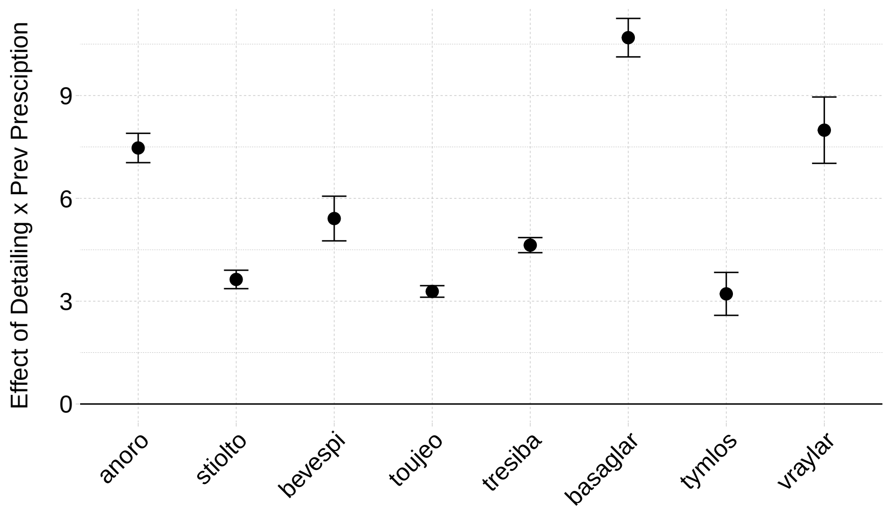
(b) Detailing Propensity by Distance to High COI AMC

Note: Panel (a) shows the fraction of physicians detailed that work at an AMC (matched by address) of each COI score. The 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 3: Physician Response to Detailing - Awareness



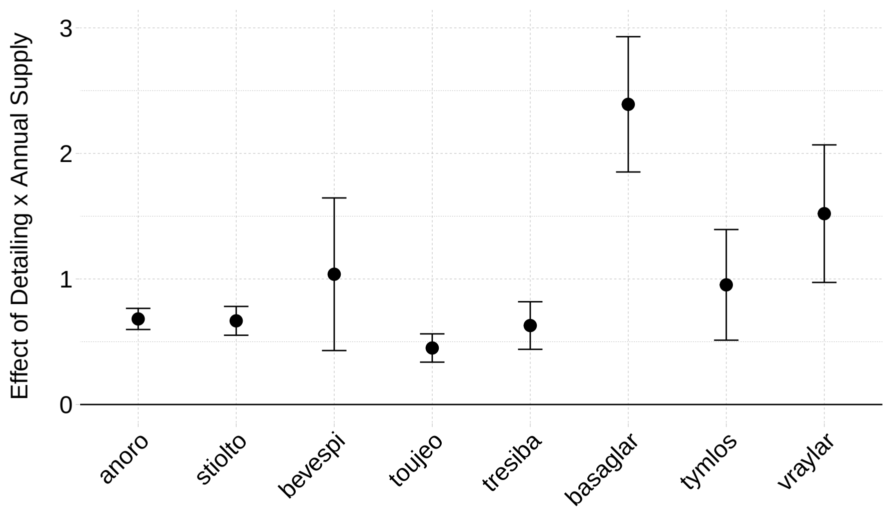
(a) Any Prescription Given No Previous Prescription



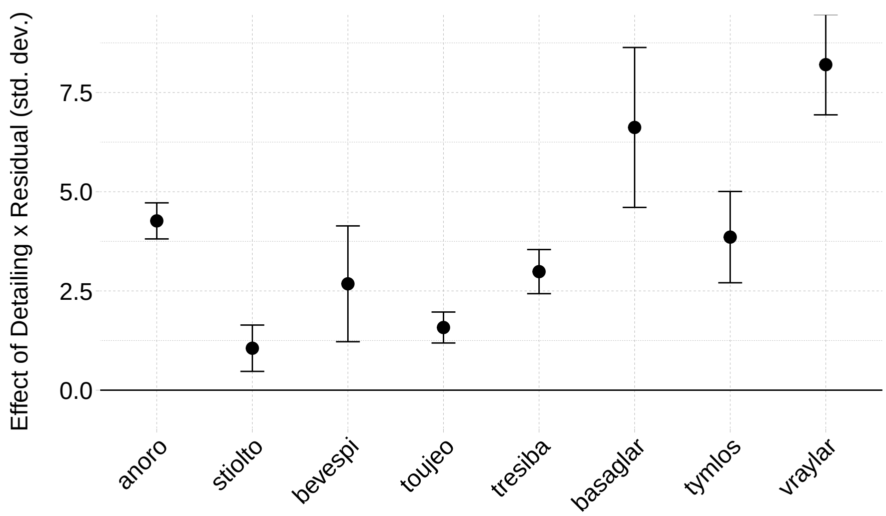
(b) Differential Share Response by Awareness

Note: 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. See Appendix Table A3 for corresponding regression results.

Figure 4: Differential Response by Experience and Beliefs



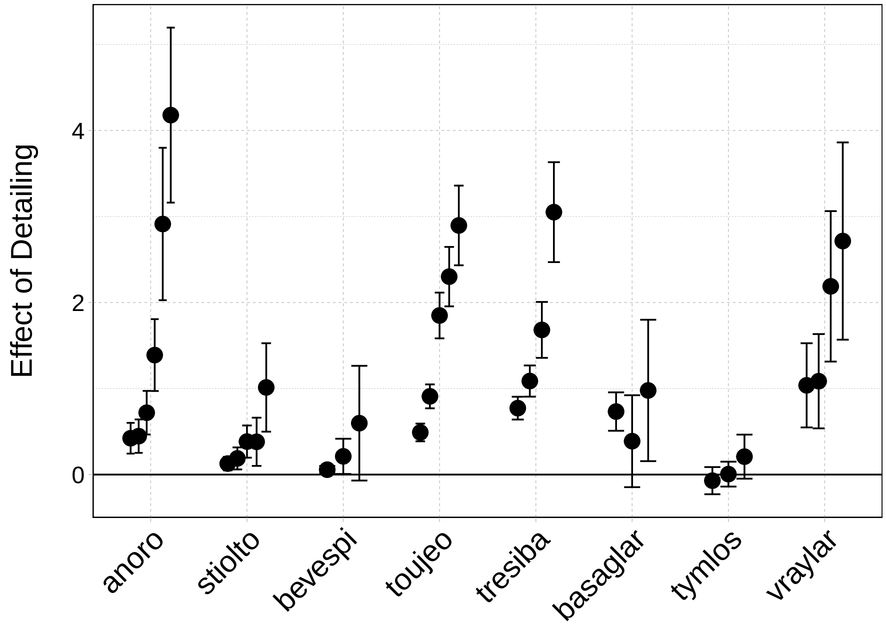
(a) Lagged Experience



(b) Lagged Mean Beliefs

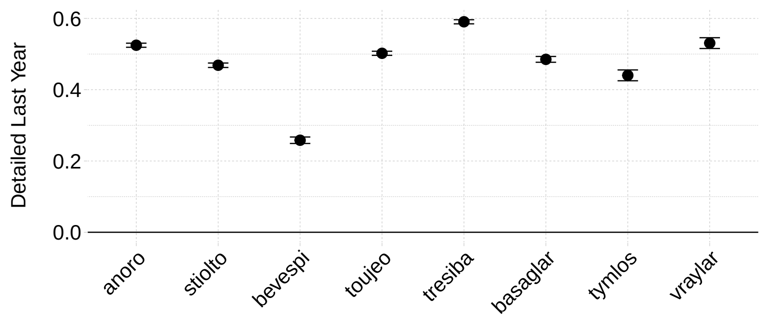
Note: This figure plots the prescription share responses by experience and prior beliefs, corresponding to the interaction terms estimated in Equation (10). Panel (a) displays the estimates for the interaction between being detailed and the lagged annual supply of the drug. Panel (b) displays the estimates 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. See Appendix Table A4 for corresponding regression results.

Figure 5: Physician Responses Over Time

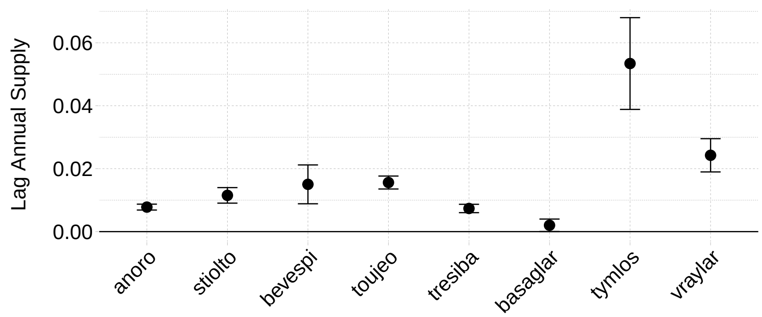


Note: This figure plots the prescription share responses to detailing over time, with each point estimate corresponding to the total effect of being detailed in each year following entry of the drug (Equation (11)). Within each drug, the point estimates for each year between entry and 2019 are plotted from left to right. The standard error bars denote 95% confidence intervals. See Appendix Table A5 for corresponding regression results.

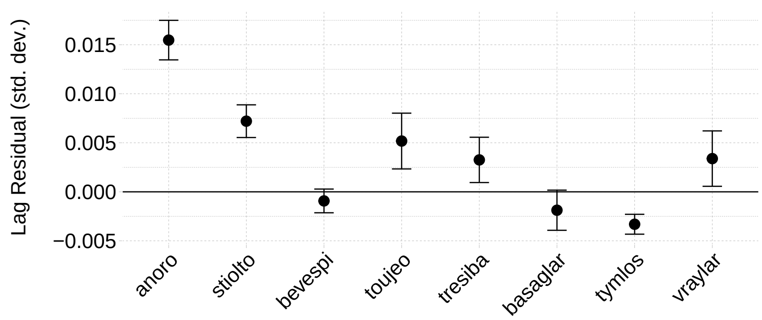
Figure 6: Firm Detailing Behavior



(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)). The three panels represent three coefficients from a single estimation per-drug. Panel (a) displays the additional probability of detailing a physician that was detailed in the prior year. Panel (b) displays the additional probability of detailing a physician with an additional annual supply prescribed in the prior year. Panel (c) 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. The standard error bars denote 95% confidence intervals. See Appendix Table A6 for corresponding regression results.