Online Appendices

The Role of Information in Pharmaceutical Advertising: Theory and Evidence

Marquardt and Ryan (2026)

A Supplementary Tables and Figures

Table A1: Summary Statistics of Physician Characteristics

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
% Main Specialty	5.3	4.6	4.7	2.5	2.5	2.4	5.3	12.4
% Male	60.1	59.7	53.2	56.0	53.7	51.6	56.0	50.8
% Top 25 School	6.4	6.2	5.5	5.9	5.6	5.3	6.7	3.6
% Top 100 School	26.2	26.2	22.9	25.0	23.8	22.7	25.2	21.3
Mean Graduation Year	1994	1995	1998	1996	1997	1998	1997	1999
% At COI$\geq$ 30 AMC	3.5	3.5	3.7	3.4	3.4	3.5	3.7	2.8
Mean Market Size	972	1,053	925	1,443	1,418	1,380	438	450

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 **??**. $MainSpecialty$ 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 **??**, 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

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Extensive Margin Response Given No Previous Prescription								
Detail	0.173***	0.126***	0.153***	0.309***	0.236***	0.162***	0.018	0.194***
	(0.022)	(0.019)	(0.024)	(0.019)	(0.018)	(0.043)	(0.018)	(0.027)
N	762360	735778	430757	620371	517874	399222	419270	155391
Panel B: Differential Share Response by Awareness (Lagged Prescription Indicator)								
Detail	-1.092***	-0.479***	-0.274	0.829***	0.409***	-0.638**	-0.770***	-0.084
	(0.360)	(0.181)	(0.312)	(0.123)	(0.157)	(0.280)	(0.256)	(0.407)
Interaction	7.470***	3.634***	5.411***	3.284***	4.635***	10.688***	3.213***	7.989***
	(0.218)	(0.137)	(0.332)	(0.086)	(0.112)	(0.286)	(0.320)	(0.493)
N	807119	749846	433012	658999	538927	414595	419695	157604

Note: 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 (**??**)). 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 (**??**)). Each estimation uses the IV strategy and includes the set of controls detailed in the main text, Section **??**. Statistical significance is based on clustered standard errors at the zip code level, with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Differential Response by Experience and Beliefs

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Experience (Lagged 365-Day Supply)								
Detail	-1.204	-3.589***	-2.506	2.833**	-0.447	-12.809***	-1.288*	2.909
	(0.952)	(1.218)	(1.949)	(1.353)	(2.453)	(2.282)	(0.781)	(3.907)
Interaction	0.682***	0.667***	1.038***	0.450***	0.629***	2.391***	0.953***	1.520***
	(0.043)	(0.059)	(0.310)	(0.057)	(0.097)	(0.275)	(0.225)	(0.279)
N	44239	13946	2253	37991	20796	15361	425	2180
Panel B: Mean Beliefs (Lagged Benchmark Residual)								
Detail	3.251***	2.956	6.378***	-1.414	0.536	-4.253	0.898	2.035
	(0.987)	(3.379)	(1.958)	(2.364)	(2.270)	(2.885)	(0.645)	(3.769)
Interaction	4.265***	1.057***	2.680***	1.579***	2.987***	6.620***	3.856***	8.202***
	(0.232)	(0.298)	(0.744)	(0.199)	(0.284)	(1.028)	(0.587)	(0.645)
N	44239	13946	2253	37991	20796	15361	425	2180

Note: This table presents the estimation results of prescription share responses by experience and prior beliefs. All regressions are estimated on the sample of doctors that have previously prescribed the rug. Each panel contains the intercept and slope term for the response to detailing in Equation (**??**) 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 uses the IV strategy and includes the set of controls detailed in the main text, Section **??**. Statistical significance based on clustered standard errors by zip code with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Physician Response to Detailing By Year

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Detail× Year 0	0.423*** (0.091)	0.128*** (0.040)	0.057** (0.022)	0.490*** (0.053)	0.772*** (0.068)	0.733*** (0.114)	-0.071 (0.081)	1.037*** (0.250)
Detail× Year 1	0.447*** (0.099)	0.188*** (0.065)	0.212** (0.104)	0.909*** (0.071)	1.087*** (0.093)	0.388 (0.273)	0.005 (0.074)	1.085*** (0.280)
Detail× Year 2	0.719*** (0.129)	0.384*** (0.096)	0.597* (0.340)	1.849*** (0.136)	1.682*** (0.166)	0.978** (0.419)	0.208 (0.131)	2.188*** (0.446)
Detail× Year 3	1.389*** (0.213)	0.381*** (0.143)		2.301*** (0.176)	3.050*** (0.296)			2.714*** (0.585)
Detail× Year 4	2.913*** (0.452)	1.013*** (0.262)		2.896*** (0.236)				
Detail× Year 5	4.178*** (0.519)							

Note: Each column represents an estimation of Equation (**??**), using the IV strategy and set of controls detailed in the main text, Section **??**. The coefficients display the total effect in each year, i.e. the third row displays the effect of detailing two years after drug entry. Statistical significance is based on zip code clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Firm Detailing Behavior

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Lag Detail	0.525*** (0.003)	0.469*** (0.003)	0.258*** (0.005)	0.502*** (0.003)	0.591*** (0.003)	0.485*** (0.004)	0.440*** (0.008)	0.531*** (0.008)
Lag Experience	0.008*** (0.000)	0.012*** (0.001)	0.015*** (0.003)	0.016*** (0.001)	0.007*** (0.001)	0.002** (0.001)	0.053*** (0.007)	0.024*** (0.003)
Lag Belief	0.015*** (0.001)	0.007*** (0.001)	-0.001 (0.001)	0.005*** (0.001)	0.003*** (0.001)	-0.002* (0.001)	-0.003*** (0.001)	0.003** (0.001)

Note: This table presents coefficients from the linear probability model specified in Equation (**??**). 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 noted in the main text, Section **??**. Statistical significance is based on zip code clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Firm Detailing Behavior By Year

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Lag Detail								
× Year 1	0.597***	0.573***	0.284***	0.668***	0.675***	0.557***	0.629***	0.552***
	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.012)	(0.011)
× Year 2	0.640***	0.537***	0.247***	0.473***	0.640***	0.456***	0.399***	0.524***
	(0.004)	(0.005)	(0.009)	(0.005)	(0.004)	(0.006)	(0.009)	(0.011)
× Year 3	0.579***	0.496***		0.481***	0.518***			0.548***
	(0.005)	(0.006)		(0.005)	(0.005)			(0.011)
× Year 4	0.420***	0.338***		0.451***				
	(0.005)	(0.007)		(0.006)				
Lag Experience								
× Year 1	0.032***	0.073***	0.090***	0.033***	0.028***	0.021**	-0.062	0.045***
	(0.007)	(0.014)	(0.013)	(0.004)	(0.003)	(0.009)	(0.083)	(0.010)
× Year 2	0.007***	0.024***	0.012***	0.019***	0.014***	0.004***	0.076***	0.025***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.001)	(0.001)	(0.008)	(0.004)
× Year 3	0.012***	0.017***		0.019***	0.007***			0.022***
	(0.001)	(0.002)		(0.002)	(0.001)			(0.003)
× Year 4	0.014***	0.015***		0.018***				
	(0.001)	(0.002)		(0.001)				
Lag Belief								
× Year 1	-0.009***	0.010***	0.000	-0.002	0.000	-0.001	0.001**	0.005***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)
× Year 2	0.012***	0.010***	-0.001	0.012***	0.008***	-0.002*	-0.005***	0.006***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
× Year 3	0.024***	0.011***		0.009***	0.012***			-0.002
	(0.002)	(0.001)		(0.002)	(0.002)			(0.002)
× Year 4	0.034***	0.007***		0.006***				
	(0.002)	(0.001)		(0.002)				

Note: The estimations follow the same specification as Table A6 but allows the three coefficients of interest in Equation (**??**) 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 zip code clustered standard errors with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Example AMSA Scorecard

amsa
American Medical Student Association
AMSA Scorecard 2014

2014 AMSA Scorecard Final Results, 1

Institution: [redacted]
Overall Grade: B
Policy Review Date: 7/3/14

Domain 1: Gifts: 3
All gifts (zero dollar limit) including items such as free meals, items of nominal value such as pens and other similar items, payment for time for travel to or time at meetings are prohibited
Domain 2: Meals: 2
No industry-funded meals of any nature or value allowed on-campus or off-campus except through provision of unrestricted educational grants to support meals and educational program.
Domain 3: Industry-Funded promotional speaking relationships: 3
Policy effectively prevents faculty from being paid by industry to do promotional speaking, or to be on industry-funded speakersΣ≤˥ bureaus.
Domain 4: Industry support of ACCME-accredited CME: 1
Industry support can be accepted with the only stipulation being that they must follow ACCME criteria.
Domain 5: Attendance of industry-sponsored promotional programs: 2
Faculty may not receive travel reimbursement for attending industry-sponsored conference. Invitees may attend dinner lectures sponsored by a vendor, however the individual cannot accept complimentary meals.
Domain 6: Industry-funded scholarships and awards: 2
Industry may provide scholarships for meeting attendance, but it may not participate in the selection of attendees.
Domain 7: Ghostwriting and honorary authorship: 3
Ghostwriting and honorary authorship are strictly prohibited.
Domain 8: Consulting and advising relationships: 3
Consulting or honoraria for speaking must take place with an explicit contract with specific deliverables, and the deliverables should be restricted to scientific issues, not marketing efforts.
Domain 9: Access of pharmaceutical sales representatives: 2
Pharmaceutical representatives are allowed to meet with faculty but the meetings must take place only in non-patient care areas and the meetings must take place by appointment only
Domain 10: Access of medical device representatives: 3
This policy effectively prohibits medical device representatives from promoting products in patient care areas though they may be there for legitimate educational purposes unrelated to marketing.
Domain 11: Conflict of interest disclosure: 2
Internal disclosure is required annually. It is not clear if there is a requirement for all faculty and staff, including those that do not do research, to provide disclosure to audiences or students.
Domain 12: Existence of an adequate COI curriculum for medical students: 2
A limited COI education is required by the institution.
Domain 13: Extension of COI policies to adjunct/courtesy faculty and affiliated hospitals/clinics: 3
This policy applies to all employees of the institution, whether full/part-time or volunteer faculty, and trainees, and it applies to them regardless of the site they are working at.
Domain 14: Enforcement and Sanctions of Policies: 2
There is a party responsible for oversight of the policy, but there are no sanctions for noncompliance included in the policy

Note: This figure shows an example 2014 Academic Medical Center COI scorecard.

B Physician Utility, Learning, and Prediction Derivations

This appendix is supplementary to main text, Section **??**. Here, 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 **??**.

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^2_{0ip}: $\mu^*_p \sim N(\mu_{0ip}, \sigma^2_{0ip})$. 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:

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

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

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

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^2_{0ip}. 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 $\tilde{d}_p \sim N(\mu^*_p, \sigma^2_D)$. In other words, detailing visits can provide information about the quality of the drug for treating 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^2_D. With normally distributed prior beliefs and detailing signals, a Bayesian updating physician will have the following posterior belief if detailed: $\mu^*_p \mid D_i = 1 \sim N(\mu_{ip}, \sigma^2_{ip})$ where

$$\mu_{ip} = \frac{\sigma^2_D}{\sigma^2_D + \sigma^2_{0ip}}\mu_{0ip} + \frac{\sigma^2_{0ip}}{\sigma^2_D + \sigma^2_{0ip}}\tilde{d}_p \tag{B.4}$$

$$\sigma^2_{ip} = \big(\frac{\sigma^2_{0ip}\sigma^2_D}{\sigma^2_{0ip} + \sigma^2_D}\big) \tag{B.5}$$

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 **??**, we derive 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 show 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:

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

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

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

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 $\frac{\partial \Delta u_{ip}}{\partial \mu_{0ip}} = -\left(\frac{\sigma_{0ip}^2}{\sigma_{0ip}^2+\sigma_D^2}\right) < 0$. This gives us prediction (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.

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:

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

This derivative is positive as long as $\tilde{d}_p \geq \mu_{0ip} - \psi\sigma_{0ip}^2\left(1+\frac{\sigma_D^2}{(\sigma_{0ip}^2+\sigma_D^2)}\right)$. 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 beliefs.

Finally, repeated detailing visits generate diminishing informational returns because each additional detail visit signal contributes less to posterior updating. With each additional signal, beliefs become more precise and closer to the true mean. Since the utility gain from detailing depends in part on the reduction in uncertainty, this gives us prediction (iv): repeated detail visits to the same physician will have diminishing returns from information.

C Robustness and Heterogeneity Appendix

This appendix is supplementary to main text, Section ??.

C.1 Controlling for Patient-Mix Appropriateness

We first address the possibility that our set of controls may not account of additional unobserved heterogeneity in relevant patient mix for a given drug. The role of the set of controls in Equations (??)-(??) is to hold other sources of physician heterogeneity fixed and isolate differential responses associated with variation in physician information at the time of detailing, $InfoChannel_{id,t-1}$. To assess the robustness of our results to additional unobserved heterogeneity in physician patient mix, we implement two complementary approaches.

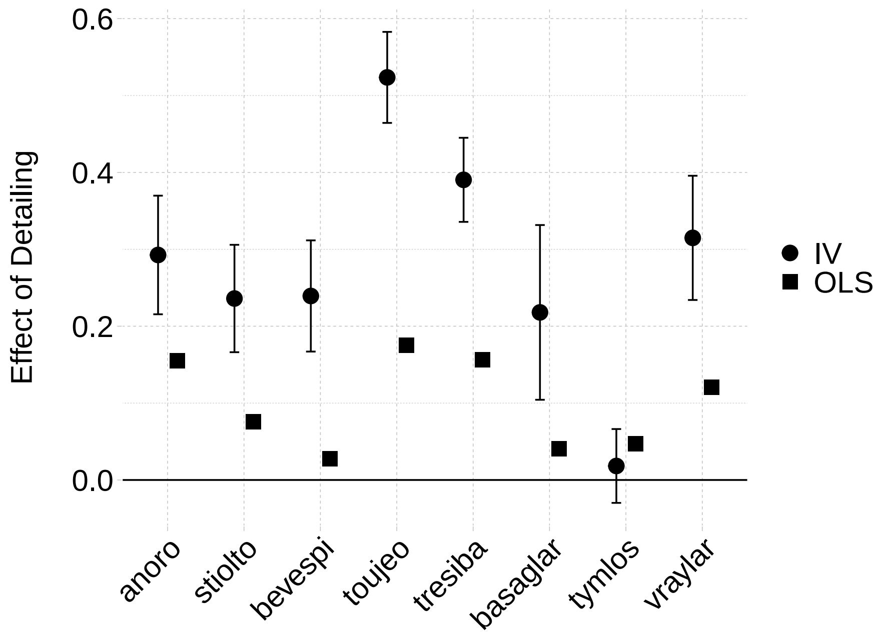
First, as mentioned in Section ??, detailing visits may be correlated with unobserved determinants of prescribing, such as patient appropriateness or anticipated responsiveness, that are not captured by our set of controls. We address this concern using the instrumental variable strategy based on the physicians' 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 the detail visit propensity (Grennan et al. (2025)).

The bias in the OLS estimate is informative of the importance of unobserved physician heterogeneity. If detailing is targeted towards physicians with a more appropriate patient mix (not captured by observed heterogeneity in X_{it}), then the OLS will be biased upward. Alternatively, if detail visits are targeted based on potential outcome levels (e.g., to those who would otherwise have had a low prescription share and also potentially respond more to detailing), the bias will go in the other direction. In Figure C1, we compare the OLS and IV estimate for the baseline effect of detailing on the probability of prescribing (Equation (??), but regardless of whether they have prescribed in the past). We find that the OLS estimate is smaller than the IV estimate, suggesting that the former channel (selective targeting based on unobservably more relevant/appropriate patient mix) is unlikely to be the dominant source of bias.[1] As shown in later Figures C3 and C4, this is also true when we condition on past

[1] This potential bias result is similar to what is found in Grennan et al. (2025) when comparing the OLS estimate to the MTE-based ATE in the context of statins.

prescribing and in the various tests for differential response by prior information: the OLS estimates have the same sign but often smaller magnitude than the IV based estimate.

Figure C1: Effect of Detailing on Prescription Share: Full Sample



Note: This figure plots estimates of the effect of detailing on the prescription share (percentage points) of all the physicians in the sample for each drug. The plot contains both OLS estimates and IV estimates that employ the same identification strategy outlined in Section 4. The error bars represent 95% confidence intervals around the point estimates.

While the OLS and IV comparison for the baseline detailing specification suggests that our set of controls capture important heterogeneity in patient mix appropriateness, it still may be the case that the interaction term $InfoChannel_{id,t-1}$ may be correlated with unobserved heterogeneity in patient mix appropriateness for the drug. For example, it could be that those with higher $InfoChannel_{id,t-1}$ levels (i.e., those who prescribed in the past, had higher prescription volume, and/or prescribed above the benchmark rate for their observed patient mix), have an unobservably more relevant/appropriate patient mix. If this were the case, then those with a higher information level proxy could respond more to detailing simply because they have a more appropriate patient mix rather than because of differences in underlying true information sets. This would show up as a positive detailing interaction effect, but would not necessarily rule out the predictions from the information-based model, and therefore lead us to incorrectly interpret the differential response as evidence against learning and information exchange.

Thus, as our second approach, we consider an alternative definition of the outcome of interest, physician prescription share, that further conditions on those that are most appropriate candidates for the drug. Specifically, we redefine the prescription share as the fraction of prescriptions for the target drug among all drugs of a particular class of drugs that are pharmacological substitutes. See Table C1 for the list of drugs we identify as pharmacological substitutes. This differs from the measure in the main analysis which is defined as the fraction of prescriptions for the target drug among all patients with the relevant chronic condition. The strength of this alternative measure is that it is plausibly less susceptible to unobserved variation in the patient population as it already conditions on the quantity prescribed within a very narrow target class of drugs rather than a more variable set of diagnosed patients. However, it also has a weakness in that it ignores substitution outside of this specified class. We use this alternative share measure both to define the outcome prescription share, $RxShare_{idt}$ in Equations (**??**) and (**??**), and to compute the residual prescription share benchmark relative to experts as discussed in Section **??**.[2]

We re-estimate the main empirical tests using this alternative definition of prescription share and present the results in Figure C2. Note that there are only four tests that rely on the prescription share definition. Panels A-D in of Figure C2 correspond to main text Figures **??**, **??**, **??**, and **??**, respectively. We find that the patterns using the alternative prescription share definition are qualitatively similar to those of the main results, with the sole exception of firm targeting by lagged beliefs, where effects are now imprecisely estimated.

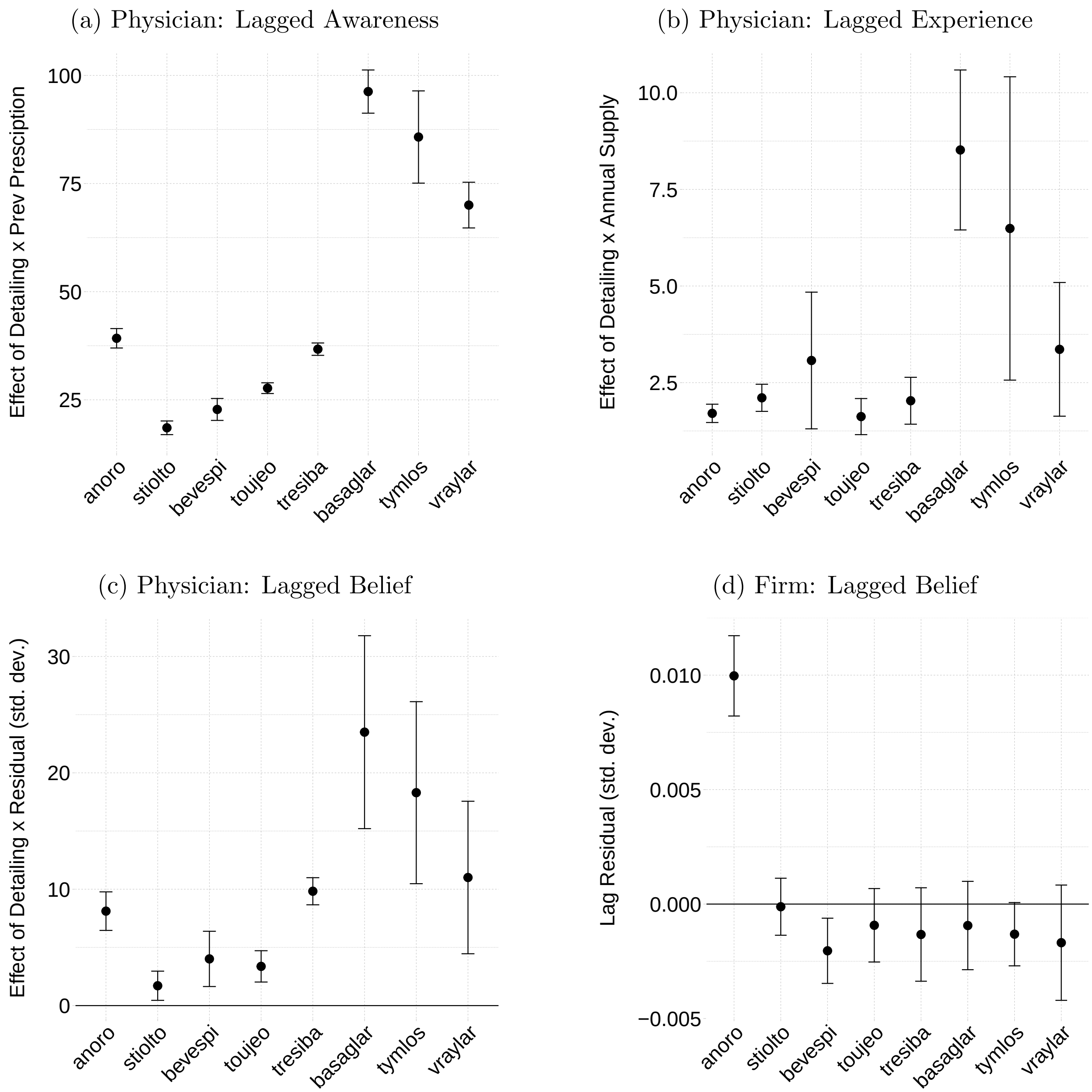
[2]This alternative prescription share measure is positively correlated with the baseline prescription share measure, though not perfectly so. Across all drugs in the sample, the correlation ranges from 0.35 to 0.50.

Table C1: List of Substitutes By Disease Category

Disease:	COPD	Diabetes	Osteoporosis	Anti-psychotic
Drug Type:	Bronchodilator Combination	Long/Medium Acting Insulin	Parathyroid Hormone Analogs	Partial Agonist
Substitutes:	**Anoro**	**Tresiba**	**Tymlos**	**Vraylar**
	Stiolto	**Toujeo**	Natpara	Abilify
	Bevespi	**Basaglar**	Forteo	Aristada
	Trelegy	Lantus		Lumatperone
	Breo	Levemir		Rexulti
	Symbicort	Semglee		Reaglia
	Wixela	Humulin		
	Advair	Novolin		
	Breztri			
	Dulera			
	Combivent			
	Airduo			
	Duoneb			
	Breyna			
	Utibron			
	Duaklir			

Note: This table shows the potential substitutes used to construct an alternative market share measure. For the drugs treating COPD, we include 15 brands of bronchodilator combinations, which contain more than one bronchodilator or a combination of a bronchodilator and a steroid. For the drugs treating diabetes, we include all formulations of long-acting insulin and generic, medium-acting insulin. For the osteoporosis drug Tymlos, we include three parathyroid hormone analogs. (A fourth parathyroid, Bonsity, was approved at the end of 2019). For the anti-psychotic drug, we include drugs that are identified as potential substitutes in Laszlovszky et al. (2021) (https://pmc.ncbi.nlm.nih.gov/articles/PMC8279990/).

Figure C2: Differential Response by Experience and Beliefs: Share Defined Within Substitutes



Note: This plots the physician responses with a re-definition of prescription share, which is the number of prescriptions for the target drug divided by the total number of prescriptions with the drug class specified in Table C1. Panels A-D in this figure correspond to main text Figures **??**, **??**, **??**, and **??**, respectively. The scales differ due to differences in how the variable is defined. Both panels show the 95% confidence intervals around the point estimates.

C.2 Additional Robustness Checks & Heterogeneity

We also consider the possibility that the data patterns reflect differences in the response to detailing across physicians that are 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 specification.

First, we re-estimate the results of the paper using alternative samples of physicians. Figures C3 and C4 illustrate how four estimates from alternative samples compare to the baseline estimates of the differential physician response to detailing.

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.

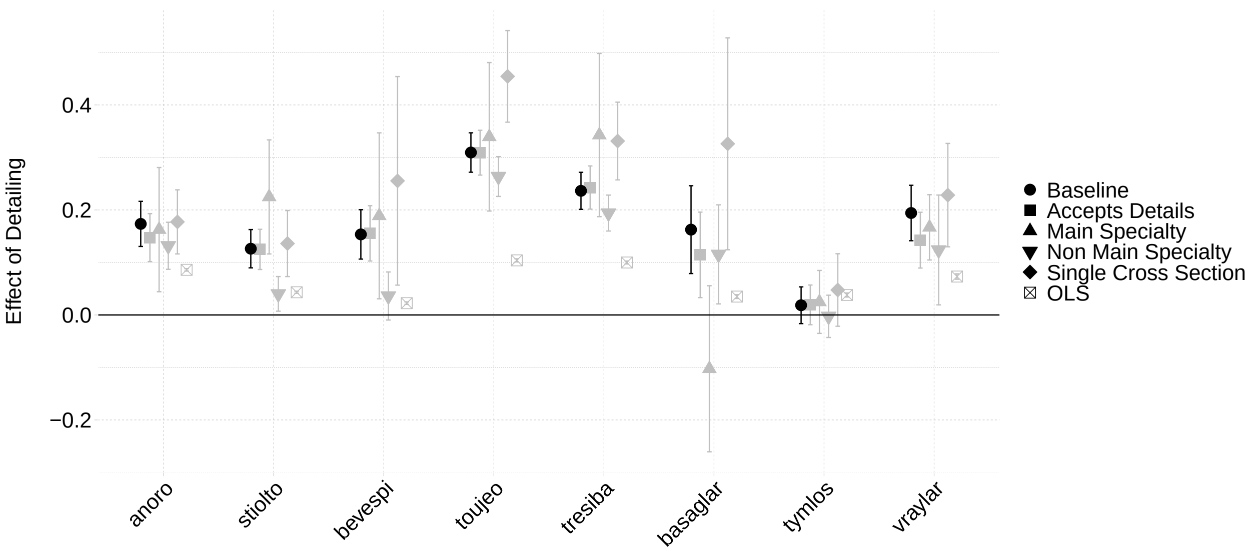
The "Single Cross Section" sample displayed in Figure C3 estimates the awareness channel tests using only a single year of data. We include this robustness check to account for the fact that our indicator for any previous prescription by the physician is an absorbing state. Thus, the composition of the sample in main text Figure **??** changes over time and physicians permanently switch from the no previous prescription to the previous prescription group in

Figure ??. 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.

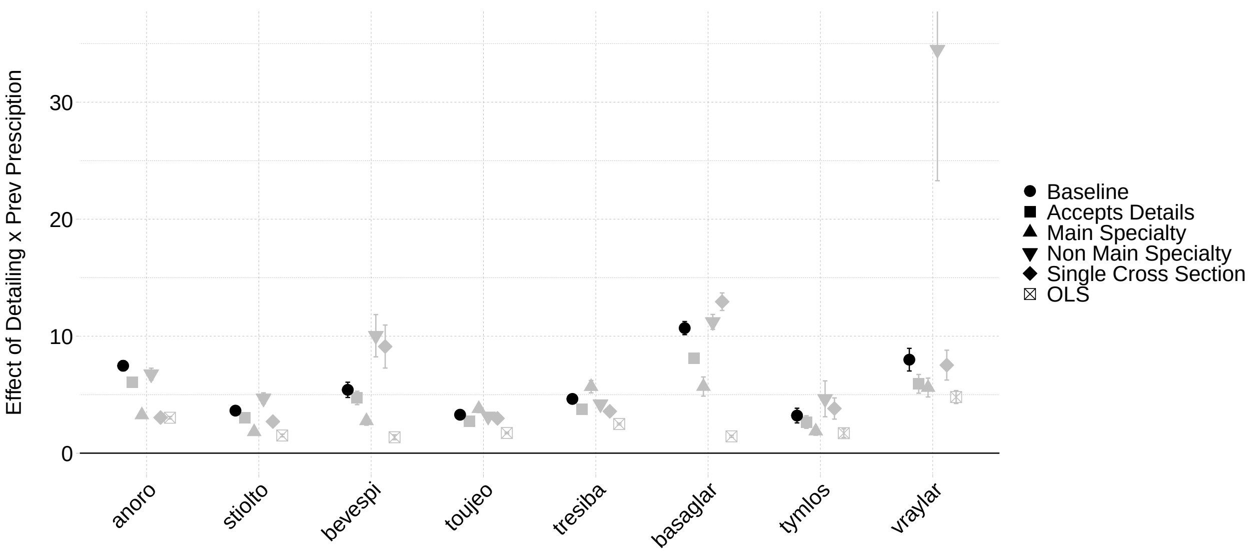
Figure C5 displays the results of the firm targeting estimation specifications for four robustness specifications: “Accepts Detail”, “Main Specialty”, “Non Main Specialty”, and “Zip Code Fixed Effect”. The first three are re-estimations of the firm targeting specifications under the physician samples 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 arise within the main specialty physician sample: for many drugs, the coefficients relating detailing to the lagged benchmark residual among specialists are imprecisely estimated. Similarly, the targeting policies are less dependent on prescription volume. Importantly, however, 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 ??, which would predict a negative relationship.

Figure C3: Physician Response to Detailing - Awareness
Robustness Specifications



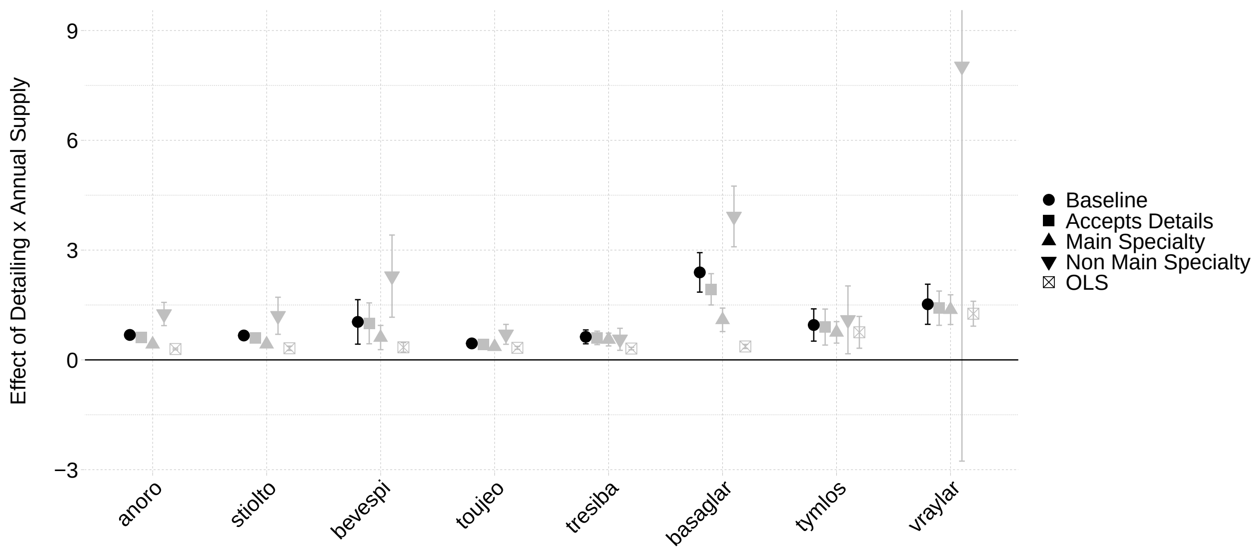
(a) Any Prescription Given No Previous Prescription



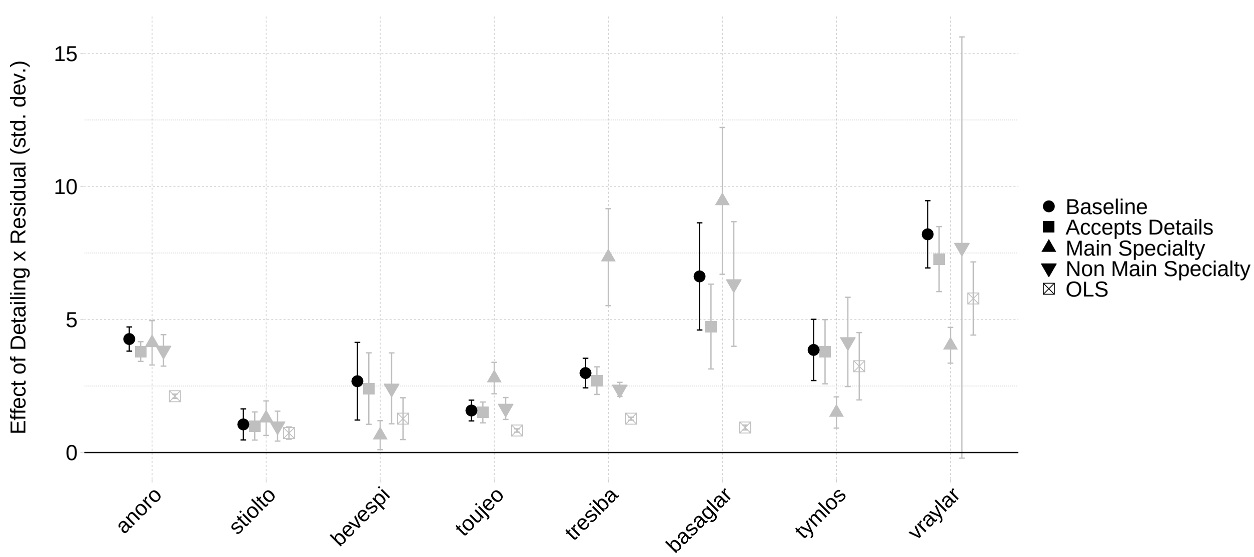
(b) Differential Share Response by Awareness

Note: This figure plots the results displayed in Figure **??** 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 from only the second year following drug entry. We also include the OLS estimate of the baseline specification. Both panels show the 95% confidence intervals around the point estimates.

Figure C4: Differential Response by Experience and Beliefs
Robustness Specifications



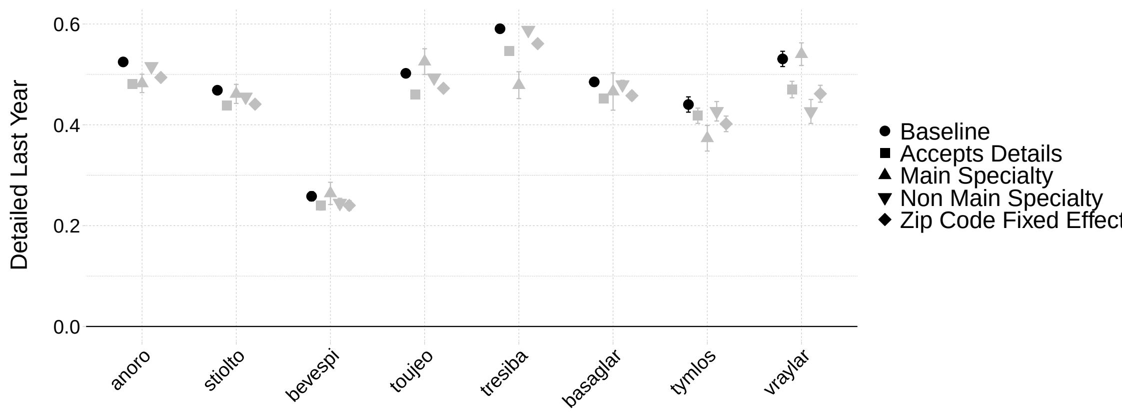
(a) Lagged Experience



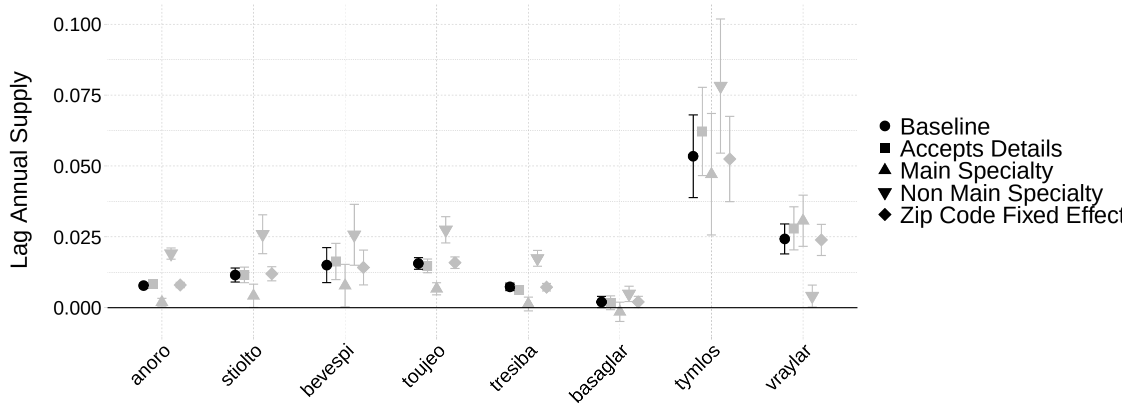
(b) Lagged Mean Beliefs

Note: This figure plots the results displayed in Figure **??** 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. We also include the OLS estimate of the baseline specification. Both panels show the 95% confidence intervals around the point estimates.

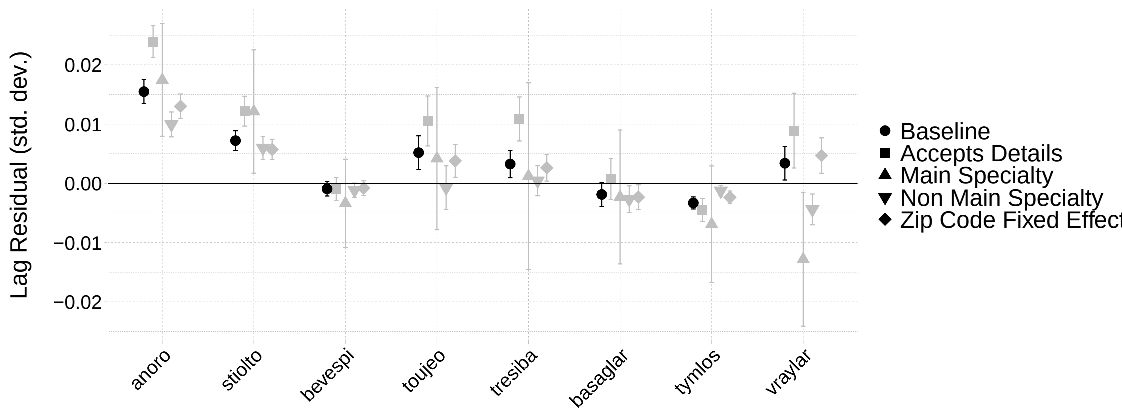
Figure C5: Firm Detailing Behavior
Robustness Specifications



(a) Prior Year Detailed



(b) Prior Year Experience



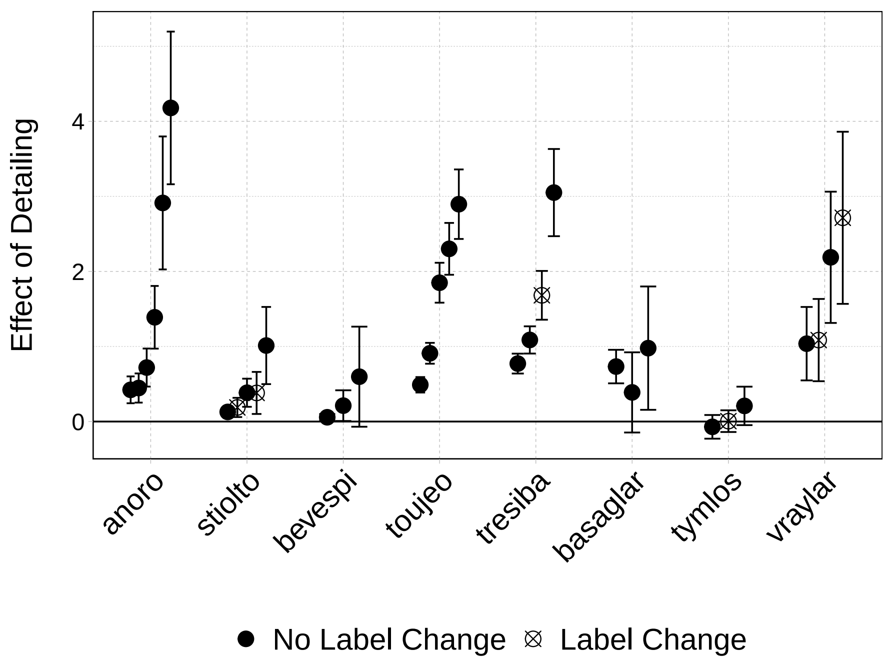
(c) Prior Year Mean Beliefs

Note: This figure plots the results displayed in Figure **??** 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.

We next consider whether the increase over time in physician response to detailing visits can be attributed to new information released about the drug. For example, Ching et al. (2016) find that the marginal effect of detailing increases in response to new information that is complex. 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 instance, 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 (Figure C6). We find that 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.

Figure C6: Physician Responses Over Time with Label Change Indications



Note: This figure plots the same estimates as shown in Figure **??**, 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.

We also consider two alternative approaches to testing how physician responses to detailing depend on their prior mean beliefs. The results are displayed in Table C2.

Table C2: Differential Response by Beliefs: Alternative Specifications

	Anoro	Stiolto	Bevespi	Toujeo	Tresiba	Basaglar	Tymlos	Vraylar
Panel A: Annual Expert Model								
Interaction	4.153***	2.002***	1.426***	1.934***	3.078***	6.759***	1.282***	3.166***
	(0.250)	(0.511)	(0.310)	(0.235)	(0.286)	(1.079)	(0.109)	(0.437)
Panel B: Flexible Interaction Specification								
Interaction|	3.851***	1.015***	6.825***	1.488***	3.170***	6.707***	4.707***	9.286***
($Resid > 0$)	(0.236)	(0.278)	(1.753)	(0.166)	(0.325)	(1.630)	(0.608)	(0.565)
Interaction|	5.719***	2.221***	0.976*	2.095***	2.746***	4.216***	0.483	4.056***
($Resid < 0$)	(0.263)	(0.186)	(0.510)	(0.316)	(0.270)	(0.733)	(0.715)	(1.049)

Note: This table presents the estimation results of prescription share responses by alternative measures of physician prior beliefs. All regressions are estimated on the 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 the “experts” annual share rather than their share in 2019. See Section **??** 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 uses the IV strategy and includes the set of controls detailed in the main text, Section **??**. Statistical significance based on clustered standard errors at the zip code level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 relatively low- and high-prescribers of the drug might respond differently to a detailing visit based on whether or not they are above or below the benchmark prediction. For all drugs, we find that among those with positive benchmark residuals, relatively high-prescribers have a significant and positive interaction, i.e. physicians that prescribe above the benchmark by more also respond more to detailing. Among those with negative benchmark residuals (prescribing below the predicted share), we find that for almost all drugs, relatively high prescribers (closer to the benchmark rate) also respond more to detailing visits. Because the prediction of the model in Section **??** is that the slope of this effect should be negative for both above and below benchmark rate prescribers, we view these results as inconsistent with the model in Section **??** and in line with the other data patterns we demonstrate.

Finally, we also 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 Tables C3, C4, and C5. The results of estimation on this extended sample are qualitatively similar to those presented in the main analysis.

Table C3: 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	0.339***	0.021***	0.016***	0.020***	0.056***	0.031***	0.051***	0.071***
	(0.028)	(0.005)	(0.004)	(0.007)	(0.008)	(0.009)	(0.013)	(0.025)
N	654259	549529	664416	414354	410101	632423	631959	121010
Panel B: Differential Share Response by Awareness (Lagged Prescription Indicator)								
Detail	-1.299***	-0.037	-0.108***	0.012	0.033	-0.033***	-0.133***	-0.615*
	(0.406)	(0.024)	(0.031)	(0.047)	(0.036)	(0.012)	(0.036)	(0.340)
Interaction	15.567***	0.620***	1.905***	4.236***	2.321***	0.558***	0.684***	4.664***
	(0.407)	(0.052)	(0.139)	(0.502)	(0.155)	(0.026)	(0.039)	(0.399)
N	674981	551118	666062	414595	410639	635875	635875	121720

Note: This table replicates the findings of Table A3 for the extended drug sample in Table A2. For more detailed notes, see Table A3.

Table C4: Differential Response by Experience and Beliefs (Extended Sample)

	Namzaric	Corlanor	Glyxambi	Xultophy	Soliqua	Repatha	Praluent	Aristada
Panel A: Experience (Lagged 365-Day Supply)								
Detail	18.780***	-0.354	-1.657***	-1.381	-1.037	-0.225	-0.618***	1.776
	(7.234)	(0.367)	(0.485)	(1.076)	(0.702)	(0.226)	(0.175)	(1.272)
Interaction	0.793**	0.241***	1.033***	0.973***	0.687***	0.226***	0.239***	0.567***
	(0.372)	(0.044)	(0.139)	(0.328)	(0.107)	(0.045)	(0.017)	(0.112)
N	20480	1583	1625	240	538	3383	3806	690
Panel B: Mean Beliefs (Lagged Benchmark Residual)								
Detail	0.365	0.318	-0.250	1.108	0.085	-0.039	0.114	3.354***
	(3.932)	(0.371)	(0.420)	(0.778)	(0.588)	(0.245)	(0.158)	(1.273)
Interaction	11.761***	0.190	0.158	0.233	0.529**	0.303***	0.425***	0.368
	(1.574)	(0.765)	(0.134)	(0.427)	(0.225)	(0.071)	(0.045)	(0.246)
N	20480	1583	1625	240	538	3383	3806	690

Note: This table replicates the findings of Table A4 for the extended drug sample in Table A2. For more detailed notes, see Table A4.

Table C5: Firm Detailing Behavior (Extended Sample)

	Namzaric	Corlanor	Glyxambi	Xultophy	Soliqua	Repatha	Praluent	Aristada
Lag Detail	0.279***	0.535***	0.455***	0.383***	0.416***	0.581***	0.393***	0.571***
	(0.004)	(0.005)	(0.003)	(0.005)	(0.004)	(0.003)	(0.004)	(0.010)
Lag Experience	0.002***	0.045***	0.036***	-0.002	0.086***	0.034***	0.046***	0.017***
	(0.001)	(0.005)	(0.005)	(0.009)	(0.007)	(0.003)	(0.007)	(0.003)
Lag Belief	0.000	0.002***	0.001	0.005***	0.000	-0.001*	-0.003***	0.004***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Note: This table replicates the findings of Table A6 for the extended drug sample in Table A2. For more detailed notes, see Table A6.

D Alternative Models Appendix

This appendix is supplementary to main text, Section ??.

D.1 Other Models of Information and Learning

We specified the model in Section ?? 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 ??, 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 relatively high-prescribing (high belief) physicians. In the costly-signaling model, the firm repeatedly targets physicians that are low-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 high-prescribing physicians, 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 visit pattern and the finding of increasing effects with respect to experience and time.

D.2 Demographics of Detailing

We examine how detail targeting is associated with physician characteristics, i.e. which physicians have high values of θ_i. To do so, 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 number of repeat visits. In all specifications we control for patient-mix characteristics, market size, physician specialty, and drug fixed-effects.[3] Results are presented in Table D1. Standard errors are two-way clustered by physician and drug.

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.

Physicians who graduated from top ranked medical school are less likely to be detailed. Conditional on being detailed once, they are also less likely to receive repeat detail visits. This is consistent with these physicians being better informed but 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).

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

Table D1: Detailing Patterns and Physician Characteristics

	Ever Detail	Detail at Entry	Number of Repeat Visits
Specialist	0.253***	0.070*	0.553***
	(0.041)	(0.023)	(0.025)
Male	0.041**	0.020**	0.176***
	(0.011)	(0.005)	(0.011)
Top 25 School	−0.025**	−0.002	−0.080***
	(0.006)	(0.006)	(0.014)
Top 100 School	0.008	−0.002	−0.053***
	(0.005)	(0.003)	(0.007)
Peer Network Size	0.033	0.010	0.126***
	(0.019)	(0.006)	(0.026)
Prior Detail By Firm	0.493***	0.282***	0.770***
	(0.059)	(0.026)	(0.011)
Grad 2000-10	−0.002	0.015	−0.176***
	(0.007)	(0.015)	(0.017)
Grad 1990-00	0.028*	0.031	−0.083***
	(0.011)	(0.019)	(0.018)
Grad 1980-90	0.048*	0.044	−0.077***
	(0.016)	(0.021)	(0.018)
Grad 1970-80	0.040*	0.048	−0.223***
	(0.017)	(0.022)	(0.019)
Grad 1960-70	0.012	0.049	−0.448***
	(0.018)	(0.023)	(0.024)
Grad 1950-60	−0.028	0.099*	−0.606***
	(0.020)	(0.033)	(0.052)
Pat Char	Y	Y	Y
Drug FE	Y	Y	Y
N	956,516	182,096	182,096

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 number of years detailed (conditional on ever being detailed). The graduation year reference bin is after 2010. Standard errors are two-way clustered by NPI and drug. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.101$.

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

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

References

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

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

Ching, A. T., Clark, R., Horstmann, I., and Lim, H. (2016). The effects of publicity on demand: The case of anti-cholesterol drugs. *Marketing Science*, 35(1):158–181.

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

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

Goldenberg, J., Han, S., Lehmann, D. R., and Hong, J. W. (2009). The role of hubs in the adoption process. *Journal of Marketing*, 73(2):1–13.

Grennan, M., Myers, K. R., Swanson, A., and Chatterji, A. (2025). No free lunch? welfare analysis of firms selling through expert intermediaries. *Review of Economic Studies*, 92(4):2537–2577.

Laszlovszky, I., Barabássy, Á., and Németh, G. (2021). Cariprazine, a broad-spectrum antipsychotic for the treatment of schizophrenia: pharmacology, efficacy, and safety. *Advances in Therapy*, 38(7):3652–3673.

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

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

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