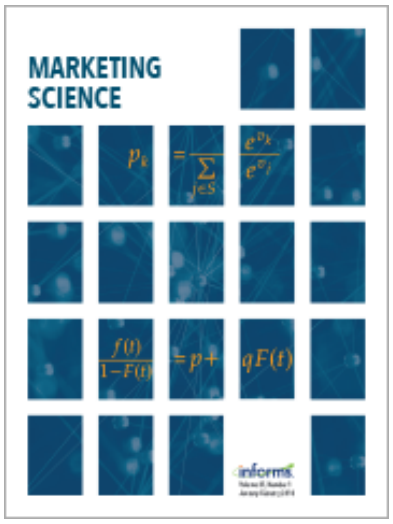

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Drug Detailing and Doctors' Prescription Decisions: The Role of Information Content in the Face of Competitive Entry

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We study the effects of information content in 59,814 pharmaceutical sales calls on doctors' prescription decisions for statins, in the face of entry of competing brands and generics, using a hierarchical Bayesian distributed lag model. We conclude that adding information content to the prescription response model improves the in- and out-of-sample performance of the model. In the first six months following generic entry, it is more effective for incumbent brands to detail on drug contraindications and indications, compared to other periods, to positively differentiate from generics. In the first six months following branded entry, it is less effective for incumbent brands to detail on drug indications and costs, given increased competitive clutter. We also document substantial heterogeneity among doctors in their response to information content. Our model is helpful for analysts to more accurately assess the effectiveness of detailing. Our empirical results are also informative for drug manufacturers as they set or change their messaging policies in response to entry and help firms to tailor their message content at the doctor level.

Data, as supplemental material, are available at https://doi.org/10.1287/mksc.2015.0971.

Keywords: personal selling; information content; pharmaceuticals; branded and generic entry; competition; distributed lag model; endogeneity; simultaneity

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1. Introduction

The scholarly literature has heavily debated the responsiveness of customers to the number of sales calls in various industries; more than half of related studies study the pharmaceutical industry (Albers et al. 2010, Hanssens et al. 2001). An important omission in this literature is the information content in sales calls and its effect on sales. By contrast, prior literature has devoted substantial attention to information content in advertisements and has related advertising content to advertising responsiveness for television, print, and banner advertising (e.g., Bertrand et al. 2010, Chandy et al. 2001, Lodish et al. 1995, Lohtia et al. 2003).

This knowledge gap is important, because firms may strategically set their sales message content. For instance, they may do so at product launch or in response to important events in a product's life cycle, such as competitive entry. In the pharmaceutical market, the context of the present study, competitive entry comes in two forms: the entry of a branded, patent-protected drug and the entry of generic drugs after the patent on a branded drug expires. Firms may adapt the information content in sales calls differentially to these two forms of entry.

In this paper, we study the effectiveness of information content discussed in pharmaceutical sales calls (often referred to as details) on prescriptions as the drug category faces changes such as the entry of branded and generic drugs. In our case, *information content* refers to the drug attributes discussed in a sales call between a sales representative and a doctor. The choice of which drug attributes to feature in a sales call is an important strategic messaging decision in the pharmaceutical industry, as well as in other industries. For instance, car manufacturers may stress mileage (Prius), performance (Porsche), or both mileage and performance (Tesla).

We not only introduce demand consequences of information content in sales calls to the marketing literature; we also extend the literature on competitive reactions with detailing to entry in the pharmaceutical market. This literature has studied the effects of competitor response to branded entry (Gatignon et al. 1989; Shankar 1997, 1999), but not the effects of the

response of branded competitors to generic entry on a competing molecule;[1] Berndt et al. (2003) describe the competitive reactions to Zantac's patent expiry, but do not measure the effectiveness of such actions. We study both the competitive responses in detailing and information content, because brands may adjust the total sales call spending, but they may also shift the message content when they face a competing molecule that goes generic.

We obtained the data for this study from IMS Health, a prime supplier of doctor-level data. Between 2002 and 2008, we observe, at the monthly level, 4,622 doctors who collectively received 59,814 detailing visits and wrote 7,900,440 total prescriptions for the top five brands in the statin category. The doctors in our panel report which drug attributes a sales representative discussed with them. From more granular information, we identify three information content components: (1) drug contraindications (i.e., information on side effects, drug and food interactions, and mechanism of action); (2) drug indications (i.e., drug efficacy, dosing, and indications); and (3) drug costs (i.e., cost effectiveness, formulary status, and price).

We propose a hierarchical Bayesian distributed lag model to model the cumulative effects of detailing volume and information content on prescriptions. We allow for differential effects of detailing and information content in the first periods after branded and generic entry. We jointly model doctor-level prescriptions, detailing volume, and the information content discussed in those details to address potential endogeneity due to unobservables and the simultaneity problem due to strategic detailing allocation. We also investigate the heterogeneity in doctors' responsiveness to information content after competitive entry.

The results show that information content matters. Adding information content to a prescription response model significantly improves the in- and out-of-sample performance of our model. We find that detailing effectiveness varies with the information content discussed and the effects of information content vary with the brand profile and market environment. Our main empirical findings are as follows.

First, in the six months following generic entry, the effectiveness of an "average detailing visit"[2] for competing branded drugs (i.e., competing molecules still under patent protection) is lower than in other periods. The market for branded drugs typically shrinks after generic entry, given the lower price of generics, causing detailing effectiveness to decrease. However, it is more effective in the first periods after generic entry for sales representatives of competing branded drugs to detail on drug contraindications and indications to emphasize their drug's (superior) performance, compared to other periods. Generics carry a lower price, but may also be perceived by doctors as lower quality than their branded counterparts. Thus, firms can benefit from emphasizing the drug attributes that positively differentiate them from these new generics.

Second, we find that in the first six months after branded entry (i.e., a new molecule under patent protection enters the category), the effectiveness of an average detailing visit for incumbent drugs is lower than in other periods. Also, the effectiveness of information content on drug indications and costs is lower for incumbent drugs compared to other periods. Branded competitive entry is likely to increase the competitive clutter of information in the market, due to an increase in overall detailing in the category, which leads to lower detailing effectiveness.

Third, we find that in the first six months after branded entry, the new drug's average detailing visit is more effective than in later periods in its life cycle. Details on information content on which the entering drug positively differentiates itself from incumbent drugs are more effective in these first periods, compared to later periods, in its life cycle. Detailing on drug costs in the first periods after launch is less effective than in later periods of the life cycle.

Fourth, based on a median split analysis, we find that upon branded entry, doctors with a high category prescription volume are more responsive to details on drug indications by branded incumbents than doctors with low category prescription volume. Similarly doctors who receive an above median number of competitive detailing visits are more responsive to details on drug indications by branded incumbents than doctors receiving a below median number of competitive detailing visits. Upon generic entry, doctors with an above median number of competitive detailing visits are more responsive to details by branded incumbents on drug costs than doctors with a below median number of competitive detailing visits. The logic behind these findings is that more active (i.e., higher category prescription volume and an above median number of competitive details) doctors learn more efficiently for the incumbent drugs about the attributes on which the new entrants differentiate themselves from incumbents.

Our results have several implications. First, it would be beneficial for analysts to take information

[1] Earlier literature (e.g., Gonzalez et al. 2008) studied the reactions of the branded drug to its own patent expiration and consequent entry of generics, but not the reactions of branded competitors still under patent protection to the patent expiry of a competing branded drug and consequent generic entry on that competing molecule.

[2] An average detailing visit refers to a detailing visit in which average information content was discussed. From our model, this variable is derived as the effect of the number of detailing visits, without taking specific information content into account.

content into account when assessing sales call effectiveness because doing so significantly improves the in- and out-of-sample performance of the prescription response model. Second, our model results inform firms' sales messaging strategies for incumbents and new entrants. For instance, contrary to the detailing policies we observe in our data, we find that in the first periods after generic entry, it is more beneficial for incumbent branded competitors to discuss drug contraindications and indications than in other periods. Third, we document the heterogeneity across doctors' responsiveness to information content, which can guide targeted messaging policies of firms.

2. Background

2.1. Sales Call Effectiveness

Personal selling is the largest marketing expenditure in many industries (Zoltners et al. 2008). Therefore, the marketing and economics literature have taken a prominent interest in analyzing sales call effectiveness across a wide range of industries (Albers et al. 2010), but most intensively so in the pharmaceutical industry (e.g., Berndt et al. 1995, Fischer and Albers 2010, Gönül et al. 2001, Manchanda et al. 2004, Mizik and Jacobson 2004, Rosenthal et al. 2003). Scholars have documented a large heterogeneity in detailing responsiveness, with some finding significantly positive effects (e.g., Gönül et al. 2001), others finding rather modest effects (e.g., Mizik and Jacobson 2004), and some finding no effect at all (e.g., Rosenthal et al. 2003). Venkataraman and Stremersch (2007) show that part of the heterogeneity in detailing responsiveness across brands and time can be explained by the strength of the drugs' attributes. In addition, many studies document heterogeneity across doctors in responsiveness to detailing (e.g., Dong et al. 2009, Manchanda et al. 2004).

2.2. Information Content in Sales Calls

The personal selling literature has largely ignored the role of sales call content, leaving it as an important area for future research (Mantrala et al. 2010, Stremersch and Van Dyck 2009). Few exceptions exist in the context of pharmaceuticals, but they only describe the information content discussed, instead of analyzing its effect on doctors' prescriptions. Ziegler et al. (1995) analyze the accuracy of 106 drug statements of sales representatives and find that 12 of those statements are incorrect, casting the promoted drug in a more favorable light. Roughead et al. (1998) find that 13 out of 64 details contain inaccurate statements. Molloy et al. (2002) instruct five sales representatives to experimentally provide details of poor, medium, or good quality to 135 doctors and find that doctors indeed recognize details of different quality. Steinman et al. (2007) examine market research forms on 116 details in the context of the promotion for off-label usage of gabapentin.

2.3. Competitive Response to Branded and Generic Entry

The current study investigates the role of information content as the category undergoes competitive entry, such as branded and generic entry, which are two major competitive events in a drug's life cycle (Berndt et al. 2003, Kappe 2014, Narayanan and Manchanda 2009).

2.3.1. Branded Entry. Shankar (1997) finds that incumbent drugs that have a leading role in a marketing mix variable should increase their marketing efforts in response to branded entry. Shankar (1999) finds that competitors react mildly to high marketing expenditures of the new branded drug to avoid an arms race in spending. He also finds that incumbents increase their marketing expenditures in response to the entry of a drug with higher relative quality. Gatignon et al. (1989) study over-the-counter drugs and find that incumbent drugs retaliate with their more effective marketing instruments and cut back on their less effective instruments in response to a new drug entry. Danaher et al. (2008) and Vakratsas et al. (2004) find that entry leads to higher competitive intensity, which decreases the effectiveness of various marketing instruments due to increased competitive clutter.

2.3.2. Generic Entry. When the patent on a branded drug expires, generics typically enter the market at a much lower price, and the price decreases further as more generic manufacturers enter (Reiffen and Ward 2005). Under the 1984 Hatch–Waxman Act, generic manufacturers may apply for exclusivity on the generic supply for 180 days after patent expiry, which they obtain if certain conditions are met. Such conditions relate to the legal procedures a generic manufacturer may have to undergo in potential patent disputes with the branded manufacturer, and the exclusivity, if granted, is a way to recover such costs. For the market we study here, statins, we observe two generic entrants on pravastatin and three generic entrants on simvastatin in the first six months after patent expiry, which goes up to 10 entrants within about a year after patent expiry.

Generic drug manufacturers need to only show bioequivalence of their drug, making it easier for generics to get approval. Bioequivalence of generics has received considerable scrutiny. Meredith (2003) reports that 20% of the available generics are not bioequivalent to their branded counterparts. Moreover, generics may differ on the excipients, product appearance, packaging, and quality control, which

vary across the firms providing the generic (Meredith 2003). Therefore, doctors, pharmacists, and patients may not perceive generics to be equivalent to their branded counterparts (Ching 2010, Kesselheim et al. 2008, Olsson and Sporrong 2012).

The study by Berndt et al. (2003) is the only study that has investigated the reactions of branded incumbents to generic entry on a competing branded drug. They find that the main competitors of Zantac (a leading drug in the H2-antagonist market) kept their marketing expenditures stable after the patent expiry, but Berndt et al. (2003) do not measure the effectiveness of these actions.

3. Data

3.1. Data Collection

From IMS Health, we obtained monthly data on prescriptions and detailing for the statin category between August 2002 and July 2008. Statins (HMG-CoA reductase inhibitors; Anatomical Therapeutic Chemical code C10AA) lower excessive cholesterol levels in the blood, particularly low density lipoprotein (LDL) cholesterol. We study the top five drugs in this category (launch date and generic molecule name in parentheses): Pravachol (October 1991; pravastatin), Zocor (December 1991; simvastatin), Lipitor (January 1997; atorvastatin), Crestor (August 2003, rosuvastatin), and Vytorin (August 2004; combination of ezetimibe and simvastatin). In our data set, across all time periods and doctors, 56% of the unit prescriptions among the top five drugs are for Lipitor, Zocor has a share of 16%, Pravachol has a share of 10%, Crestor has a 9% share, and Vytorin also has a 9% share.

The data set includes a panel of 4,622 doctors (general practitioners and specialists) and is representative of the population of office-based doctors in the continental United States. It contains, for each month and each doctor in the panel, the number of total prescriptions doctors write (7,900,440 in total, which includes both new and refill prescriptions), the number of details they receive (59,814 in total), and the information content discussed in each of the details.

IMS Health collects the monthly number of prescriptions from pharmacies and reports them as "projected" prescriptions. This projection corrects for the nonexhaustive coverage (coverage is approximately 70%) of pharmacy outlets through an algorithm unknown to the researchers, yielding a different multiplier for each month, doctor, and brand. Because this multiplier is one or greater than one, our prescription data include zeros and continuous values of one or greater. Figures WA1 and WA2 in Web Appendix A (available as supplemental material at https://doi.org/10.1287/mksc.2015.0971) show, for each brand, the distribution of the average number of monthly total prescriptions across doctors and the total prescriptions over time.

Table 1 Principal Component Analysis Reveals Three Information Content Components

Component	Eigenvalue	% of variance explained	Cumulative % of variance explained
1	3.49	29.09	29.09
2	1.27	10.59	39.67
3	1.01	8.45	48.12
4	0.96	8.01	56.13
5	0.93	7.73	63.86
6	0.75	6.23	70.09
7	0.72	6.02	76.11
8	0.66	5.48	81.59
9	0.60	5.00	86.60
10	0.59	4.92	91.51
11	0.54	4.49	96.01
12	0.48	3.99	100.00

Doctors in the panel report the number of details and their information content on an IMS Health website. To collect accurate and complete data, IMS Health trains doctors in their panel before participation and only compensates doctors who report complete data on time. It regularly reminds them via telephone or email. IMS Health extensively monitors the quality of recruiting panel members, data collection and verification, and the representativeness of the sample. Also, they occasionally contact the doctor to verify reported information.

Doctors report information content along 12 product attributes potentially discussed in the detailing visit: efficacy, dosage, indications, new form, price, safety, side effects, interactions, mechanism of action, patient profile, cost effectiveness, and formulary status. We perform a principal component analysis (PCA) on these product attributes, based on all detailing visits in our data, pooled across brands and doctors, for two main reasons: (1) including all attributes in our empirical model would make estimation infeasible; (2) several attributes are discussed often in the same call, suggesting components of information content at a conceptually higher level.

Table 1 shows the results of a PCA with (1) an eigenvalue of >1 as the cutoff criterion and (2) varimax rotation. The three extracted components jointly explain 48% of the variation in the information content. Table 2 provides the component loadings. For interpretation, we use the conventional cutoff value of 0.5 and highlight the cells that are above the cutoff value. We label the components "*drug contraindications*," "*drug indications*," and "*drug costs*." In medicine, contraindications present reasons to withhold the drug from a patient, whereas indications present reasons to administer the drug.

Table 2 Three Information Content Components Represent Drug Contraindications, Indications, and Costs

Information content	Detailing on drug contraindications	Detailing on drug indications	Detailing on drug costs
Detailing on efficacy	0.057	0.678	0.088
Detailing on dosing	0.211	0.703	0.085
Detailing on indications	0.105	0.758	0.013
Detailing on new form	0.393	0.012	0.180
Detailing on price	0.391	0.043	0.509
Detailing on safety	0.472	0.193	0.241
Detailing on side effects	0.766	0.150	0.033
Detailing on interactions	0.792	0.094	0.066
Detailing on mechanism of action	0.586	0.238	0.152
Detailing on patient profile	0.181	0.470	0.372
Detailing on cost effectiveness	0.337	0.084	0.655
Detailing on formulary status	−0.018	0.130	0.787

Notes. Component loadings after varimax rotation with Kaiser normalization are shown. The highlighted cells indicate component loadings above 0.5.

The highest-loading attribute in the first component, *drug contraindications*, is the IMS Health variable interactions. Commonly discussed interactions in sales calls include interactions of the drug with food (e.g., fat content), other diseases (e.g., diabetes), or other drugs (e.g., various fibrates). Side effects are unintended events that may create discomfort (e.g., flushes) or harm a patient (e.g., cause liver damage). The mechanism of action also loads on drug contraindications, because it is very informative for all interactions that may arise and for the likelihood of side effects occurring in certain patients.

The highest-loading attribute in the second component, *drug indications*, is the IMS Health variable indications, which here refers more narrowly to the diseases and symptoms for which the drug is approved by the U.S. Food and Drug Administration (FDA) (e.g., high LDL cholesterol). Efficacy is the ability of the drug to produce the desired therapeutic effect (e.g., the decrease in LDL). The variable dosing refers to the drug dosages available and the specific indications they target (e.g., different LDL levels require specific dosage strengths to be effectively treated).

The third component, *drug costs*, is related to the drug's price, cost effectiveness, and formulary status. Drug price represents a cost to the payer (e.g., insurance or the government) and/or patient, depending on the level of copay that exists for that drug. The copay depends on the formulary status, which refers to the payer's preference for a drug and determines the cost of the drug to the payer and patient. Cost effectiveness refers to whether a drug is worth its costs.

We construct the information content variables for our empirical model by using the results of the PCA to compute for each detailing visit the component scores (with mean zero and standard deviation one) on all three components. When a doctor receives multiple detailing visits for a specific brand in a single month, we sum the component scores across details to obtain the total amount of information discussed related to each component.

Our observation period contains three major events of special relevance to the effectiveness of information content in sales calls: (1) the entry of Crestor in August 2003; (2) the entry of Vytorin in August 2004; (3) the generic entry after the patent expiry for Pravachol and Zocor in April and June 2006, respectively. Based on clinical evidence and press reports from the time around these events, Crestor was superior to incumbent drugs on drug indications, while being comparable on drug contraindications and costs (Consumer Reports 2014, Quirk et al. 2003). Vytorin was superior to incumbent drugs on both drug contraindications and indications, while being comparable on drug costs (Martinez 2004, Thomaselli 2004). When generics for pravastatin and simvastatin entered the market at substantially lower prices than incumbent branded drugs, Pravachol and Zocor quickly lost market share (see Figure WA2 in Web Appendix A) and ended their detailing efforts almost completely.

3.2. Descriptives

Table 3 shows for each information content component the average percentage of sales calls in which the sales representative and doctor discuss at least one of the three attributes that have a component loading of above 0.5, as shown in Table 2 (Table WA1 in Web Appendix A shows the average percentage of sales calls in which each of the individual attributes are discussed). For instance, the first row of Table 3 indicates that during 39% of the sales conversations about Pravachol, the sales representative and doctor discuss at least one of the three attributes that strongly relate to drug contraindications. Table 3 provides two insights. First, the average percentage of sales calls in which the sales representative and doctor discuss drug indications (84%) is much higher compared to

Table 3 Average Percentage of Sales Calls That Discuss at Least One of the Three Attributes That Define Each Information Content Component

	Detailing on drug contraindications (%)	Detailing on drug indications (%)	Detailing on drug costs (%)
Pravachol	39	79	33
Zocor	24	81	35
Lipitor	27	84	37
Crestor	34	85	40
Vytorin	30	86	44
Average across brands	30	84	39

Table 4 Percentage Change in Average Percentage of Sales Calls That Discuss at Least One of the Three Attributes That Define Each Information Content Component Six Months After the Event Compared to Six Months Before

		Event (%)		
Brand	Detailing or component	Entry Crestor	Entry Vytorin	Generic entry Pravachol/Zocor
Pravachol	# details	−22	−20	—
	Detailing on drug contraindications	−9	−5	—
	Detailing on drug indications	−7	−6	—
	Detailing on drug costs	−7	10	—
Zocor	# details	1	−4	—
	Detailing on drug contraindications	−7	1	—
	Detailing on drug indications	0	−6	—
	Detailing on drug costs	−4	12	—
Lipitor	# details	4	4	20
	Detailing on drug contraindications	11	−16	−2
	Detailing on drug indications	−2	1	−2
	Detailing on drug costs	−9	−3	12
Crestor	# details	—	−14	5
	Detailing on drug contraindications	—	−5	−9
	Detailing on drug indications	—	−6	1
	Detailing on drug costs	—	−11	−1
Vytorin	# details	—	—	−1
	Detailing on drug contraindications	—	—	−8
	Detailing on drug indications	—	—	0
	Detailing on drug costs	—	—	−4
Average across brands	# details	−6	−9	8
	Detailing on drug contraindications	−2	−6	−6
	Detailing on drug indications	−3	−4	0
	Detailing on drug costs	−7	2	2

Note. We do not report changes in detailing and information content for Pravachol and Zocor after their patent expiry because they almost completely stopped their detailing efforts after patent expiry.

drug contraindications (30%) and costs (39%). Thus, sales representatives discuss attributes related to reasons to prescribe the drug (drug indications) more often than those related to reasons that may withhold the doctor from prescribing the drug (drug contraindications) and those related to costs. In fact, the three attributes related to indications are discussed more often for each brand than all other individual attributes (see Table WA1 in Web Appendix A). Second, there is less variation across drugs in the percentage of sales calls in which the sales representative and doctor discuss drug indications, compared to drug contraindications and costs.

Table 4 shows for each information content component the percentage change in the average percentage of sales calls that discuss at least one of the three attributes, with a component loading above 0.5, six months after branded or generic entry compared to six months before (Table WA2 in Web Appendix A shows the corresponding changes at the individual attribute level).[3] A few patterns arise. First, in the six months following the entry of Crestor, sales representatives of all incumbents discuss drug costs less frequently with doctors compared to the six months before the entry. This decrease is mainly driven by a reduction in the discussion of the price attribute (see Table WA2 in Web Appendix A). The pattern for drug contraindications and indications is mixed across incumbents. Second, in the six months following the entry of Vytorin, three of the four incumbents discuss drug contraindications and indications less frequently than six months before the entry. Vytorin entered the market with a more favorable profile on contraindications and indications compared to the incumbent drugs (Martinez 2004, Thomaselli 2004). Third, in the six months after the generic entry on Pravachol and Zocor, sales representatives for all incumbent brands discuss contraindications less frequently than six months before the generic entries. Fourth, the average reactions across brands at the bottom of Table 4 show that incumbents decrease their detailing efforts after branded entry (a 6% decrease after the entry of Crestor and a 9% decrease after the entry of Vytorin), which is contrary to the finding of Shankar (1999). However, incumbents increase their detailing efforts by 8% after generic entry.

[3] Note that Pravachol and Zocor (almost) completely stopped detailing after their patents expired and generic drugs entered. Therefore, we do not report their changes in detailing and information content after generic entry in Table 4.

4. Model

4.1. Prescription Response Model

We model the cumulative effects of detailing and information content on prescriptions because, detailing may affect prescriptions in the current and future periods. The distributed lag modeling framework, which captures both contemporaneous and carryover effects of explanatory variables, is well suited for this goal (e.g., Hanssens et al. 2001, Leeflang et al. 2000). We model the prescriptions of doctor i for drug j at time t by a hierarchical Bayesian distributed lag model

$$\begin{aligned} TRx_{ijt} = {} & \alpha_{0ij} \\ & + [(\alpha_{1ij} + \alpha_{2ij} Entry\ Crestor_t + \alpha_{3ij} Entry\ Vytorin_t \\ & \quad + \alpha_{4ij} Generic\ Entry_t) \times \#Details_{ijt}] \\ & + [(\alpha_{5ij} + \alpha_{6ij} Entry\ Crestor_t + \alpha_{7ij} Entry\ Vytorin_t \\ & \quad + \alpha_{8ij} Generic\ Entry_t) \\ & \quad \times Detailing\ on\ Drug\ Contraindications_{ijt}] \\ & + [(\alpha_{9ij} + \alpha_{10ij} Entry\ Crestor_t + \alpha_{11ij} Entry\ Vytorin_t \\ & \quad + \alpha_{12ij} Generic\ Entry_t) \\ & \quad \times Detailing\ on\ Drug\ Indications_{ijt}] \\ & + [(\alpha_{13ij} + \alpha_{14ij} Entry\ Crestor_t + \alpha_{15ij} Entry\ Vytorin_t \\ & \quad + \alpha_{16ij} Generic\ Entry_t) \\ & \quad \times Detailing\ on\ Drug\ Costs_{ijt}] \\ & + \alpha_{17ij} Entry\ Crestor_t + \alpha_{18ij} Entry\ Vytorin_t \\ & + \alpha_{19ij} Generic\ Entry_t \\ & + \alpha_{20ij} X_{ijt} + \alpha_{21ij} TRx_{ijt-1} + \varepsilon_{ijt}. \end{aligned} \tag{1}$$

The variables are defined as follows:

TRx_{ijt} Total number of prescriptions (including new and refill prescriptions) written by doctor i, for drug j, in month t

$Entry\ Crestor_t$ Dummy taking the value 1 in the first p months after the entry of Crestor, starting in August 2003, 0 otherwise

$Entry\ Vytorin_t$ Dummy taking the value 1 in the first p months after the entry of Vytorin, starting in August 2004, 0 otherwise

$Generic\ Entry_t$ Dummy representing the entry of generic drugs for Pravachol and Zocor; takes the value 1 for q months starting in May 2006, 0 otherwise

$\#Details_{ijt}$ Number of detailing visits for doctor i, drug j, in month t

$Detailing\ on\ Drug\ Contraindications_{ijt}$ Sum of the component scores on drug contraindications across details for doctor i, drug j, in month t

$Detailing\ on\ Drug\ Indications_{ijt}$ Sum of the component scores on drug indications across details for doctor i, drug j, in month t

$Detailing\ on\ Drug\ Costs_{ijt}$ Sum of the component scores on drug costs across details for doctor i, drug j, in month t

X_{ijt} Set of control variables for doctor i, drug j, in month t.

The error term ε_{ijt} follows a multivariate normal (MVN) distribution across brands, $\varepsilon_{ijt} \sim \text{MVN}(0, \Sigma)$, and the α-parameters are doctor and brand specific, with $(\alpha_{0ij}, \ldots, \alpha_{21ij})' \sim \text{MVN}(\bar{\alpha}_j, \Sigma_{\alpha_j} I)$, where I is the identity matrix. Note that we define the dummies $Entry\ Crestor_t$ and $Entry\ Vytorin_t$ to be equal to 1 in the p months after their entry, and $Generic\ Entry_t$ to be equal to 1 in the q months after generic entry. In our empirical application, we select the optimal value of p and q based on an information criterion, which we discuss in more detail in §4.3. Note that we do not include separate dummies for the generic entry of Pravachol and Zocor in our model, because (1) these events were very close together, (2) separate dummies add little explanatory power, and (3) our findings for these dummies were not stable, whereas the other parameter estimates in the model with separate dummies were similar to those resulting from our current model.

The variable $\#Details_{ijt}$ can be interpreted as the number of detailing visits in which average information content is discussed. Although our main focus is on information content, it is important to control for the number of details because it may also capture relationship building, customer rapport, and drug reminder effects, among others. The parameters α_{1ij}, α_{5ij}, α_{9ij}, and α_{13ij} measure the base short-term effects of the number of details and information content. The parameters representing the interaction effects of branded and generic entry with detailing and information content measure how the effects of detailing and information content change compared to the base effects in the first p and q periods after branded and generic entry. The parameter α_{21ij} represents the carryover effect and captures both refill prescriptions and other carryover effects (Richard and Van Horn 2004). In the absence of any entry events, the cumulative effect of the number of details for doctor i and brand j can be computed by $\alpha_{1ij}/(1-\alpha_{21ij})$ and similarly so for the information content.

We operationalize the control variables X_{ijt} as follows. We include a linear trend taking the value one in the first period and the value 72 in the last period of our data. We include competitive detailing in the same period for each of the competitors. We also account for the release of the initial results of the ENHANCE study on January 14, 2008, which had a negative impact on the sales of Vytorin and positively affected sales for the generic simvastatin (Greenland and Lloyd-Jones 2008). Specifically, we include seven

monthly dummies for Vytorin to account for the impact of this information release in the last seven months of the data.

4.2. Endogeneity and Simultaneity

Detailing allocation is typically endogenous (e.g., Dong et al. 2009, Stremersch et al. 2013) due to unobservable factors that may jointly impact prescriptions and detailing (Villas-Boas and Winer 1999). Because we are the first to study the impact of information content in sales calls, we do not know whether information content is endogenous as well, but consider it likely for this to be the case. In addition, simultaneity is a concern, as detailing may be a function of the random intercept and detailing effectiveness parameter (Manchanda et al. 2004).

We address endogeneity and simultaneity concerns by jointly modeling prescriptions, detailing, and information content. We allow for a full covariance matrix between prescriptions, detailing, and information content to control for unobservable factors (see Kumar et al. 2011, Stremersch et al. 2013). We also include the constant and the detailing effectiveness parameter as explanatory variables in the detailing equation, as well as the information content effectiveness parameters in the information content equations (as introduced by Manchanda et al. 2004).[4] Note that the number of details is a count variable and the information content variables are continuous. Therefore, we use a hierarchical Bayesian negative binomial model for the number of details

$$P(\#Details_{ijt} = l \mid \nu_{ijt}, \gamma_j) = \frac{\Gamma(\gamma_j + l)}{\Gamma(\gamma_j)\Gamma(l+1)}\left(\frac{\gamma_j}{\gamma_j + \nu_{ijt}}\right)^{\gamma_j}\left(\frac{\nu_{ijt}}{\gamma + \nu_{ijt}}\right)^{l}, \quad (2)$$

with overdispersion parameter γ_j and

$$\nu_{ijt} = \exp[\beta_{0ij}\log(W_{1ijt}) + \beta_{1j}\alpha_{0ij} + \beta_{2j}\alpha_{1ij} + \omega_{ijt}]. \quad (3)$$

The term W_{1ijt} contains a constant, lagged detailing, lagged detailing for each of the competitors, and the dummies *Entry Crestor*$_t$, *Entry Vytorin*$_t$, and *Generic Entry*$_t$; α_{0ij} represents the base prescription volume of doctor i for brand j and α_{1ij} represents the detailing responsiveness of doctor i for brand j (i.e., the detailing responsiveness based on all periods, except the first p months after the branded entry events and the first q months after the generic entry event). The β_{0ij}-parameters are doctor and brand specific, with $(\beta_{0ij})' \sim \text{MVN}(\bar{\beta}_j, \Sigma_{\beta_j} I)$, whereas β_{1j} and β_{2j} only differ across brands for identification purposes.

[4] Empirical model testing showed that information content was not affected by the constant from the prescription response model.

Note that if the overdispersion parameter in (2) goes to infinity, this model reduces to a Poisson model.

We use a hierarchical Bayesian linear model for the information content. We specify the equation only for the first information content component, drug contraindications, but estimate similar equations for the other information content components.

$$\textit{Detailing on Drug Contraindications}_{ijt} = \delta_{0ij} W_{2ijt} + \delta_{1j}\alpha_{5ij} + \zeta_{ijt}, \quad (4)$$

with $(\delta_{0ij})' \sim \text{MVN}(\bar{\delta}_j, \Sigma_{\delta_j} I)$, where W_{2ijt} contains a constant, a lagged dependent variable, lagged competitive dependent variables, and the three dummies for branded and generic entry, and α_{5ij} represents the responsiveness of doctor i for brand j to the discussion of contraindications.

The error terms in Equations (1), (3), and (4) are jointly distributed; $[\varepsilon_{ijt}, \omega_{ijt}, \zeta_{ijt}] \sim \text{MVN}(0, \Phi)$. Therefore, the complete covariance matrix for the prescription, detailing, and the three information content equations for five brands is a 25×25 variance–covariance matrix. Hence, we assume a parametric form for the endogenous variables, and the identification is based on both the chosen functional form in Equations (2)–(4) and the parametric (i.e., multivariate normal) assumption on the covariance matrix.[5]

4.3. Estimation and Model Selection

We use Bayesian estimation to simultaneously estimate Equations (1)–(4). We use a combination of Gibbs and Metropolis–Hastings steps and for the Metropolis–Hastings steps we use Resenthal's (2011) method to speed up convergence. We discuss the estimation steps and choice of priors in Web Appendix B. We account for the left censoring of one of our dependent variables, as the number of prescriptions is a continuous variable censored at zero from below. We omit the first period from our estimation sample due to the inclusion of the lagged prescriptions variable in our model.

One remaining empirical question in our model is to select the optimal values of p and q, representing the length of the dummies for the entry of Crestor/Vytorin and the entry of generic drugs. As we estimate our model using Bayesian techniques, we select the optimal length of these dummies by a fully Bayesian information criterion that takes all of the draws in the Bayesian estimation as well

[5] Ideally, we include some instrumental variables into the model. However, these instruments need to affect detailing (but not prescriptions) and vary across doctors and time. Such instruments are hard to identify (see Dong et al. 2009). Using the parametric and functional form assumptions is an alternative way to address the endogeneity problem. We thank the associate editor for this suggestion.

as the prior information into account. We use the Watanabe–Akaike, or widely available, information criterion (WAIC) (see Gelman et al. 2013, Watanabe 2010). The WAIC is a fully Bayesian alternative to the popular Akaike and deviance information criteria and computes the fit of the model based on the log posterior density adjusted by a penalty for the number of parameters due to overfitting. Specifically, we compute the model complexity penalty by the difference between the posterior mean of the deviance and the deviance calculated at the posterior mean of the parameters. Furthermore, we compare the in- and out-of-sample performance of the models with and without the inclusion of information content. We compare the in-sample performance based on the WAIC and the out-of-sample performance by estimating our model on the first 66 periods of our data and using the last six periods for holdout sample validation. We use the mean absolute prediction error (MAPE) to evaluate the relative performance of both models.

5. Results

5.1. Model Selection

We estimated several alternative models to test for the optimal values of p (the dummy length for branded entry) and q (the dummy length for generic entry). We estimated a total of nine different models with p equal to 3, 6, or 12 and q equal to 3, 6, or 12. The values of 3, 6, and 12 are based on the entry patterns we observed, where two generic manufacturers (Watson and Teva) entered on pravastatin and three (Ranbaxy, Dr. Reddy, and IVAX, now Teva) entered on simvastatin in the first 3 months, and between months 6 and 12, six and seven additional generic manufacturers entered on pravastatin and simvastatin, respectively. All results are based on 90,000 iterations of the Markov chain Monte Carlo sampler, of which we use the first 60,000 for burn-in. Based on the methods suggested by Gelman and Rubin (1992) and Geweke (1992), we conclude that each model has converged (see Web Appendix C for details). Based on the WAIC, we select the model with $p = 6$ and $q = 6$ as our optimal model.[6]

Comparing the first period of six months with months 7–12 after entry on information content, we did not find any changes in information content that showed a significant pattern. For both drugs that lost patent protection, the number of prescriptions dropped by more than 70% in the first six months after patent expiry, after which it remained relatively stable for Pravachol and slightly decreased further for Zocor. We also retrieved results of the model with $p = 12$ and $q = 12$ that were similar at slightly lower significance levels to the results of the model with $p = 6$ and $q = 6$. Thus, we conclude that an event window of six months is appropriate.

5.2. Results for the Detailing and Information Content Equations

Tables 5–8 present the population mean parameters of the models for the number of details and information content in Equations (2)–(4) to address the endogeneity and simultaneity concerns (the population variance parameters are in Tables WD1–WD4 in Web Appendix D).

Table 5 shows that many variables are significantly related to the number of details (with average content) for each of the five brands. First, the lagged number of details for the same brand has a significantly positive effect for each brand on the number of details in the next period. Second, lagged competitive detailing generally has a positive effect on the number of details. Third, the three entry events have a significant impact on the number of details. In line with the descriptive findings discussed in §3.2, we find that the number of details for incumbents decreases, on average, in the first six months after branded entry. However, contrary to the descriptive findings in §3.2, we do not find that incumbents increase their detailing after generic entry. Fourth, Zocor and Lipitor allocate more detailing visits to doctors with a high base prescription volume. Fifth, three of the five drugs significantly increase detailing based on doctors' responsiveness to detailing. Note that Manchanda et al. (2004) found the opposite effect, which they attribute to the absence of competitive detailing in their data. We verify their assertion that with the inclusion of competitive detailing, doctors with higher detailing responsiveness receive more detailing visits. Sixth, the overdispersion parameters indicate substantial overdispersion.

The results for the three information content components in Tables 6–8 show the following. First, for all three information content components, the lagged value of the respective information content component for the same brand is significant for at least four out of five brands, indicating persistence in the messaging of sales representatives to doctors. Second, we find some significant competitive reactions for all information content components, but the signs of these competitive reactions are mixed. Third, although the results for the entry events are, on average, in line with the descriptive findings in §3.2, not all of these results are significant. Overall, we find evidence

[6] We can use the WAIC to obtain the probabilities that each of the alternative models is best by computing the Akaike weights (Burnham and Anderson 2004). The results indicate that the probability that our selected model is best is equal to 1, and the next best model has a probability of 3.34×10^{-6}.

Table 5 Population Mean Parameters for the Number of Details Equation

	Pravachol	Zocor	Lipitor	Crestor	Vytorin
Constant	**−3.5727** (−3.9121, −3.2780)	**−2.8652** (−3.2970, −2.4911)	**−2.9539** (−3.0968, −2.7662)	**−2.4399** (−2.7546, −2.1573)	**−2.6847** (−2.9324, −2.5028)
# details Pravachol ($t-1$)	**0.8163** (0.6804, 0.9443)	**0.1983** (0.1331, 0.2742)	**0.0505** (0.0190, 0.1073)	−0.0126 (−0.0409, 0.0406)	**0.1525** (0.0622, 0.2539)
# details Zocor ($t-1$)	**0.2988** (0.1977, 0.3914)	**0.8272** (0.7754, 0.8893)	**0.2297** (0.1837, 0.2523)	**0.2515** (0.1708, 0.3478)	**0.2078** (0.1078, 0.2663)
# details Lipitor ($t-1$)	**0.0903** (0.0387, 0.1716)	**0.3409** (0.3234, 0.3706)	**0.7175** (0.6617, 0.7574)	**0.0891** (0.0443, 0.1168)	**0.2600** (0.2028, 0.3229)
# details Crestor ($t-1$)	**0.3141** (0.2469, 0.3991)	**0.0906** (0.0399, 0.1438)	**0.1676** (0.1171, 0.2109)	**0.4128** (0.3054, 0.4916)	**0.1803** (0.1232, 0.2494)
# details Vytorin ($t-1$)	**0.1742** (0.1431, 0.2483)	**0.1159** (0.0344, 0.2513)	**0.0977** (0.0690, 0.1278)	**0.0996** (0.0476, 0.1437)	**0.6873** (0.5659, 0.7739)
Entry Crestor	**−0.1134** (−0.1357, −0.1010)	−0.0123 (−0.0420, 0.0284)	**0.0477** (0.0185, 0.0780)	**0.4123** (0.3679, 0.4628)	
Entry Vytorin	**−0.1555** (−0.1804, −0.1392)	**−0.0374** (−0.0833, −0.0046)	0.0289 (−0.0044, 0.0526)	**−0.0567** (−0.1042, −0.0319)	**0.2881** (0.2447, 0.3231)
Generic entry	**−0.0903** (−0.1357, −0.0511)	**−0.1686** (−0.2142, −0.0987)	**0.0983** (0.0166, 0.1681)	−0.0061 (−0.0309, 0.0482)	**−0.0374** (−0.0794, −0.0013)
Base volume	0.0476 (−0.0474, 0.1243)	**0.3622** (0.0629, 0.5727)	**0.1042** (0.0306, 0.2144)	0.3893 (−0.2595, 1.0392)	0.1281 (−0.1268, 0.5066)
Responsiveness to # details	−0.2794 (−0.7287, 0.1087)	−0.0323 (−0.4491, 0.3779)	**0.5616** (0.1066, 0.9145)	**1.1775** (0.6284, 1.7344)	**1.1411** (0.6654, 1.6042)
Overdispersion	**0.0892** (0.0449, 0.1120)	**0.3455** (0.2084, 0.4362)	**0.2821** (0.1921, 0.3537)	**0.3055** (0.1972, 0.3546)	**0.2736** (0.2255, 0.3323)

Notes. The table shows posterior means (and 95% confidence intervals) for the number of details equation. For values in bold, the 95% confidence interval does not contain zero.

Table 6 Population Mean Parameters for the Detailing on Drug Contraindications Equation

	Pravachol	Zocor	Lipitor	Crestor	Vytorin
Constant	**0.0039** (0.0022, 0.0057)	−0.0008 (−0.0026, 0.0010)	0.0028 (−0.0011, 0.0056)	**0.0076** (0.0058, 0.0084)	0.0018 (−0.0014, 0.0055)
Detailing on drug contraindications Pravachol ($t-1$)	−0.0038 (−0.0136, 0.0041)	0.0053 (−0.0060, 0.0186)	0.0037 (−0.0096, 0.0130)	0.0071 (−0.0011, 0.0225)	−0.0107 (−0.0238, 0.0008)
Detailing on drug contraindications Zocor ($t-1$)	**0.0054** (0.0000, 0.0124)	**0.0387** (0.0285, 0.0442)	**0.0113** (0.0058, 0.0183)	**0.0359** (0.0274, 0.0457)	0.0033 (−0.0050, 0.0115)
Detailing on drug contraindications Lipitor ($t-1$)	**0.0071** (0.0027, 0.0118)	**−0.0088** (−0.0131, −0.0034)	**0.0374** (0.0300, 0.0443)	**0.0074** (0.0018, 0.0122)	−0.0007 (−0.0068, 0.0043)
Detailing on drug contraindications Crestor ($t-1$)	−0.0001 (−0.0037, 0.0083)	0.0051 (−0.0035, 0.0103)	**−0.0157** (−0.0226, −0.0076)	**0.0432** (0.0385, 0.0509)	0.0052 (−0.0025, 0.0112)
Detailing on drug contraindications Vytorin ($t-1$)	**−0.0049** (−0.0121, −0.0007)	**−0.0067** (−0.0134, −0.0009)	**−0.0158** (−0.0256, −0.0070)	**−0.0167** (−0.0243, −0.0118)	**0.0547** (0.0420, 0.0624)
Entry Crestor	**−0.0043** (−0.0106, −0.0004)	**−0.0060** (−0.0096, −0.0034)	**0.0195** (0.0103, 0.0240)	**0.0289** (0.0211, 0.0356)	
Entry Vytorin	−0.0037 (−0.0069, 0.0007)	−0.0010 (−0.0030, 0.0006)	**−0.0156** (−0.0257, −0.0048)	−0.0010 (−0.0069, 0.0041)	**0.0176** (0.0130, 0.0214)
Generic entry	−0.0010 (−0.0049, 0.0046)	**0.0027** (0.0003, 0.0047)	**−0.0058** (−0.0086, −0.0010)	**−0.0065** (−0.0114, −0.0038)	**−0.0080** (−0.0117, −0.0029)
Responsiveness to drug contraindications	−0.0151 (−0.1050, 0.0461)	0.0006 (−0.0777, 0.0609)	**−0.2582** (−0.3287, −0.1300)	−0.0949 (−0.1700, 0.0057)	−0.0739 (−0.1623, 0.0057)

Notes. The table shows the posterior means (and 95% confidence intervals) for the detailing on drug contraindications equation. For values in bold, the 95% confidence interval does not contain zero.

for mixed reactions across incumbents to branded and generic entry. Fourth, the responsiveness of doctors to information content components generally does not significantly affect which information content component is discussed with the doctor. Hence, doctors are predominantly targeted based on their responsiveness to detailing visits in which average content is discussed, not based on their responsiveness to specific information content components.

5.3. Results for the Prescriptions Equation

Table 9 shows the population mean parameters for the prescription response model in Equation (1), and Table WD5 in Web Appendix D shows the population

Table 7 Population Mean Parameters for the Detailing on Drug Indications Equation

	Pravachol	Zocor	Lipitor	Crestor	Vytorin
Constant	0.0017 (−0.0002, 0.0028)	**0.0032** (0.0005, 0.0059)	**0.0038** (0.0025, 0.0049)	0.0008 (−0.0013, 0.0020)	0.0036 (−0.0006, 0.0063)
Detailing on drug indications Pravachol ($t-1$)	**0.0091** (0.0014, 0.0190)	**0.0258** (0.0165, 0.0419)	**0.0152** (0.0019, 0.0235)	0.0090 (−0.0019, 0.0215)	0.0001 (−0.0148, 0.0117)
Detailing on drug indications Zocor ($t-1$)	0.0033 (−0.0033, 0.0073)	**0.0311** (0.0237, 0.0395)	−0.0031 (−0.0099, 0.0022)	0.0026 (−0.0023, 0.0094)	−0.0042 (−0.0104, 0.0020)
Detailing on drug indications Lipitor ($t-1$)	**0.0076** (0.0035, 0.0131)	0.0050 (−0.0002, 0.0085)	**0.0460** (0.0408, 0.0553)	0.0043 (−0.0014, 0.0103)	0.0028 (−0.0037, 0.0099)
Detailing on drug indications Crestor ($t-1$)	0.0009 (−0.0048, 0.0025)	−0.0054 (−0.0107, 0.0003)	−0.0043 (−0.0121, 0.0105)	**0.0578** (0.0498, 0.0647)	−0.0041 (−0.0140, 0.0006)
Detailing on drug indications Vytorin ($t-1$)	−0.0035 (−0.0105, 0.0014)	**−0.0164** (−0.0225, −0.0088)	0.0025 (−0.0067, 0.0083)	**−0.0123** (−0.0181, −0.0053)	**0.0702** (0.0562, 0.0839)
Entry Crestor	**−0.0029** (−0.0053, −0.0006)	**0.0063** (0.0030, 0.0080)	−0.0021 (−0.0061, 0.0024)	**0.0137** (0.0098, 0.0173)	
Entry Vytorin	−0.0026 (−0.0056, 0.0003)	**−0.0081** (−0.0129, −0.0049)	**0.0043** (0.0021, 0.0076)	**−0.0052** (−0.0085, −0.0028)	**0.0178** (0.0134, 0.0226)
Generic entry	**0.0026** (0.0005, 0.0053)	**−0.0045** (−0.0094, −0.0018)	−0.0006 (−0.0061, 0.0025)	0.0015 (−0.0031, 0.0038)	0.0019 (−0.0020, 0.0062)
Responsiveness to drug indications	0.0094 (−0.0593, 0.0593)	−0.0270 (−0.1122, 0.0623)	−0.0721 (−0.1837, 0.0339)	0.0421 (−0.0508, 0.1156)	−0.0831 (−0.1715, 0.0182)

Notes. The table shows posterior means (and 95% confidence intervals) for the detailing on drug indications equation. For values in bold, the 95% confidence interval does not contain zero.

Table 8 Population Mean Parameters for the Detailing on Drug Costs Equation

	Pravachol	Zocor	Lipitor	Crestor	Vytorin
Constant	0.0008 (−0.0009, 0.0020)	−0.0004 (−0.0052, 0.0029)	**0.0019** (0.0005, 0.0030)	**0.0041** (0.0013, 0.0064)	**0.0054** (0.0041, 0.0068)
Detailing on drug costs Pravachol ($t-1$)	0.0041 (−0.0022, 0.0127)	−0.0092 (−0.0195, 0.0060)	**−0.0176** (−0.0313, −0.0030)	**−0.0164** (−0.0249, −0.0038)	−0.0050 (−0.0244, 0.0172)
Detailing on drug costs Zocor ($t-1$)	−0.0040 (−0.0096, 0.0021)	**0.0370** (0.0292, 0.0440)	−0.0035 (−0.0150, 0.0036)	**0.0069** (0.0011, 0.0126)	**0.0163** (0.0050, 0.0254)
Detailing on drug costs Lipitor ($t-1$)	**−0.0035** (−0.0077, −0.0007)	0.0007 (−0.0046, 0.0045)	**0.0356** (0.0309, 0.0439)	0.0066 (−0.0012, 0.0108)	0.0041 (−0.0025, 0.0094)
Detailing on drug costs Crestor ($t-1$)	0.0019 (−0.0006, 0.0063)	0.0037 (−0.0015, 0.0113)	−0.0001 (−0.0079, 0.0107)	**0.0524** (0.0478, 0.0608)	0.0075 (−0.0023, 0.0124)
Detailing on drug costs Vytorin ($t-1$)	0.0003 (−0.0022, 0.0059)	**0.0067** (0.0020, 0.0129)	**0.0147** (0.0094, 0.0239)	0.0031 (−0.0015, 0.0093)	**0.0609** (0.0487, 0.0721)
Entry Crestor	−0.0012 (−0.0021, 0.0004)	**−0.0102** (−0.0124, −0.0087)	**−0.0207** (−0.0247, −0.0168)	0.0026 (−0.0019, 0.0067)	
Entry Vytorin	**0.0039** (0.0014, 0.0068)	**0.0074** (0.0015, 0.0127)	**−0.0043** (−0.0078, −0.0015)	**−0.0131** (−0.0185, −0.0090)	**0.0125** (0.0085, 0.0167)
Generic entry	0.0015 (−0.0003, 0.0050)	**0.0042** (0.0022, 0.0059)	**0.0130** (0.0086, 0.0229)	0.0026 (−0.0003, 0.0051)	0.0007 (−0.0011, 0.0044)
Responsiveness to drug costs	−0.0300 (−0.0761, 0.0380)	0.0038 (−0.0668, 0.0870)	**−0.1293** (−0.2153, −0.0188)	−0.0058 (−0.0819, 0.0509)	−0.0915 (−0.1837, 0.0092)

Notes. The table shows posterior means (and 95% confidence intervals) for the detailing on drug costs equation. For values in bold, the 95% confidence interval does not contain zero.

variance parameters. We omit the results for the full covariance matrix for the error terms between the prescriptions, detailing, and information content equations because of its size (25×25). Next, we discuss the results in Table 9, which is divided into six different panels.

5.3.1. Main Results. Panel (i) of Table 9 shows the base contemporaneous effects of the number of detailing visits and information content on prescriptions (i.e., these are the main effects with the entry variables equal to zero). The number of detailing visits with average information content has a significantly positive effect on prescriptions for all brands. The effect is lowest for the oldest drug Pravachol (0.2874) and highest for the newest drug Vytorin (0.7981). The results for information content indicate that the base

Table 9 Population Mean Parameters for the Prescriptions Equation

	Pravachol	Zocor	Lipitor	Crestor	Vytorin
(i) Base contemporaneous effects of number of details and information content					
# details	**0.2874** (0.1441, 0.4504)	**0.6048** (0.4836, 0.7159)	**0.3319** (0.2003, 0.4552)	**0.6738** (0.5607, 0.7883)	**0.7981** (0.6818, 0.9045)
Detailing on drug contraindications	−0.0384 (−0.1888, 0.1341)	−0.0251 (−0.1417, 0.0937)	0.0316 (−0.1356, 0.1867)	−0.0368 (−0.1602, 0.0783)	0.0171 (−0.1750, 0.1413)
Detailing on drug indications	0.0852 (−0.0299, 0.2197)	**−0.1361** (−0.2636, −0.0240)	0.1044 (−0.0144, 0.2308)	**0.1594** (0.0423, 0.2743)	0.0141 (−0.0907, 0.1296)
Detailing on drug costs	−0.0191 (−0.1634, 0.1382)	**0.1696** (0.0469, 0.2593)	−0.0242 (−0.1693, 0.0862)	0.0932 (−0.0205, 0.2122)	0.0871 (−0.0071, 0.1939)
(ii) Carryover effects					
Prescriptions $(t-1)$	**0.3286** (0.3184, 0.3369)	**0.5854** (0.5673, 0.6067)	**0.3396** (0.3222, 0.3503)	**0.5519** (0.5321, 0.5669)	**0.6068** (0.5879, 0.6280)
(iii) Contemporaneous effects of detailing and information content in the first six months after entry Crestor					
# details × *Entry Crestor*	**−0.2327** (−0.3938, −0.0085)	**−0.2754** (−0.4214, −0.1577)	**−0.2400** (−0.4204, −0.0697)	0.1303 (−0.0329, 0.3013)	
Detailing on drug contraindications × *Entry Crestor*	0.0090 (−0.2343, 0.1910)	0.0000 (−0.1424, 0.1400)	−0.0174 (−0.2670, 0.2068)	0.0977 (−0.0911, 0.2548)	
Detailing on drug indications × *Entry Crestor*	**−0.3918** (−0.6176, −0.1223)	−0.1086 (−0.2558, 0.0281)	**−0.2449** (−0.3980, −0.1068)	**0.2860** (0.1086, 0.4587)	
Detailing on drug costs × *Entry Crestor*	−0.0542 (−0.2703, 0.1507)	**−0.1970** (−0.3740, −0.0617)	**−0.2417** (−0.4060, −0.0317)	**−0.3457** (−0.5177, −0.1489)	
(iv) Contemporaneous effects of detailing and information content in the first six months after entry Vytorin					
# details × *Entry Vytorin*	**−0.4777** (−0.6950, −0.2272)	**−0.5080** (−0.6282, −0.3792)	−0.0953 (−0.2835, 0.0651)	**−0.1550** (−0.2816, −0.0128)	**0.1780** (0.0133, 0.2938)
Detailing on drug contraindications × *Entry Vytorin*	0.0438 (−0.2411, 0.2386)	−0.0332 (−0.2101, 0.1039)	0.0474 (−0.2148, 0.2296)	−0.0537 (−0.2059, 0.1030)	**0.4414** (0.2696, 0.5907)
Detailing on drug indications × *Entry Vytorin*	0.1173 (−0.1409, 0.3030)	0.0524 (−0.0689, 0.1878)	−0.0369 (−0.2448, 0.1346)	−0.0905 (−0.2250, 0.0374)	**0.3267** (0.1619, 0.4932)
Detailing on drug costs × *Entry Vytorin*	−0.2778 (−0.5375, 0.0280)	**−0.1749** (−0.3533, −0.0217)	0.1166 (−0.1234, 0.3295)	**−0.2131** (−0.3287, −0.0748)	**−0.1806** (−0.3046, −0.0326)
(v) Contemporaneous effects of detailing and information content in the first six months after generic entry					
# details × *Generic entry*			**−0.2203** (−0.3942, −0.0443)	**−0.3736** (−0.5248, −0.2377)	**−0.4316** (−0.5330, −0.3177)
Detailing on drug contraindications × *Generic entry*			**0.1828** (0.0154, 0.3912)	**0.1591** (0.0361, 0.3104)	0.0412 (−0.0873, 0.1748)
Detailing on drug indications × *Generic entry*			**0.2546** (0.0540, 0.4176)	0.0777 (−0.0334, 0.1691)	**0.1585** (0.0347, 0.3037)
Detailing on drug costs × *Generic entry*			0.0772 (−0.0809, 0.2444)	−0.0022 (−0.0890, 0.0779)	**0.1415** (0.0657, 0.1878)

effect of discussing drug contraindications is insignificant for all brands. The base effect for discussing drug indications is positive for Crestor (0.1594) and negative for Zocor (−0.1361), and insignificant for the remaining three brands. The base effect of discussing drug costs is only significantly positive for Zocor (0.1696).

Panel (ii) in Table 9 shows significantly positive carryover effects of prescriptions for all brands. The effect is lowest for Pravachol (0.3286) and highest for Vytorin (0.6068). We can use these carryover effects to compute the cumulative effects of detailing and information content. For example, the cumulative effects of detailing range from 0.4281 (Pravachol) to 2.0298 (Vytorin).

Panels (iii)–(v) show the differential effectiveness of the number of details and information content in the first six months after branded and generic entry. First, we find that after the entry of Crestor and Vytorin, the effectiveness of the number of details with average information content decreases for the incumbents. This finding is in line with Danaher et al. (2008) and Vakratsas et al. (2004), who find that branded entry increases the competitive intensity (which we also find in our data), which in turn decreases marketing effectiveness due to increased competitive clutter. The effectiveness of the number of detailing visits for Vytorin is significantly higher in the first six months of its life cycle (0.1780), compared to later periods, and the effectiveness of the number of detailing visits is also higher (though not significantly) for Crestor in the first six months of its life cycle, compared to later periods (0.1303). This finding is in line with Narayanan et al. (2005) who find that detailing is

Table 9 (Continued)

	Pravachol	Zocor	Lipitor	Crestor	Vytorin
			(vi) Control variables		
Constant	**−2.7938** (−3.0428, −2.4567)	**−0.5550** (−0.7092, −0.3566)	**5.9629** (5.7484, 6.3851)	**−5.9933** (−10.5198, −1.8875)	**−6.2196** (−8.5270, −3.9055)
Trend	**−0.0832** (−0.0974, −0.0609)	**−0.1146** (−0.1211, −0.1081)	**−0.0512** (−0.0577, −0.0462)	**0.0203** (0.0068, 0.0351)	**0.0784** (0.0733, 0.0842)
Competitive # details Pravachol		**−0.1271** (−0.2256, −0.0327)	**0.2057** (0.0661, 0.3349)	−0.0852 (−0.1608, 0.0351)	**−0.4795** (−0.6199, −0.3114)
Competitive # details Zocor	0.0481 (−0.0272, 0.1069)		0.0702 (−0.0106, 0.1633)	**−0.2376** (−0.3026, −0.1682)	**−0.3177** (−0.4041, −0.1905)
Competitive # details Lipitor	**0.0501** (0.0081, 0.1197)	−0.0716 (−0.1104, 0.0081)		**−0.0698** (−0.0967, −0.0228)	−0.0182 (−0.0821, 0.0700)
Competitive # details Crestor	−0.0421 (−0.1171, 0.0335)	**0.1876** (0.1103, 0.2629)	**0.1705** (0.0848, 0.2272)		**−0.1418** (−0.1988, −0.0842)
Competitive # details Vytorin	−0.0131 (−0.0827, 0.0505)	−0.0560 (−0.1593, 0.0177)	0.0852 (−0.0026, 0.1758)	**0.0851** (0.0358, 0.1196)	
Entry Crestor	**−0.4222** (−0.4720, −0.3256)	**−0.1773** (−0.3101, −0.1088)	**0.1263** (0.0315, 0.2091)	**−0.7232** (−0.6619, −0.7902)	
Entry Vytorin	0.0293 (−0.0555, 0.1205)	**−0.1396** (−0.2205, −0.0294)	0.0506 (−0.0106, 0.1745)	**0.2686** (0.1376, 0.3757)	**−0.5483** (−0.4992, −0.5927)
Generic entry	**−2.3536** (−2.5081, −2.1705)	**−0.6359** (−0.7032, −0.5372)	**0.2739** (0.1955, 0.3773)	**0.4659** (0.3539, 0.5567)	**1.0883** (1.0094, 1.1495)
Dummy January 2008					**0.2713** (0.2525, 0.3044)
Dummy February 2008					**−0.3281** (−0.3459, −0.3069)
Dummy March 2008					**−0.2850** (−0.3193, −0.2517)
Dummy April 2008					**−0.7870** (−0.8080, −0.7594)
Dummy May 2008					**−0.8748** (−0.8917, −0.8542)
Dummy June 2008					**−1.1020** (−1.1242, −1.0826)
Dummy July 2008					**−1.0206** (−1.0466, −0.9944)

Notes. The table shows posterior means (and 95% confidence intervals) for the prescriptions equation. For values in bold, the 95% confidence interval does not contain zero.

more effective at the beginning of the life cycle. The finding is also analogous to the increased effectiveness of TV advertising for new as opposed to established products (Lodish et al. 1995). Chessa and Murre (2007) find that the increased advertising effectiveness for new products is due to novel and coherent product information.

Second, after the entry of Crestor and Vytorin, we do not find significant changes in incumbents' effectiveness of discussing drug contraindications. However, we find that it is less effective for competitors to discuss drug indications in the first periods after the entry of Crestor than in other periods (this effect is significant for Pravachol (−0.3918) and Lipitor (−0.2449), and insignificant for Zocor (−0.1086)). We also find that in the first six months after Crestor and Vytorin enter, it is less effective for their competitors to discuss drug costs, compared to other periods. In the case of Crestor, this effect is significant for Zocor (−0.1970) and Lipitor (−0.2417), and insignificant for Pravachol (−0.0542); in the case of Vytorin, this effect is significant for Zocor (−0.1749) and Crestor (−0.2131), and insignificant for Pravachol (−0.2778) and Lipitor (0.1166). The competitive clutter argument also applies to these findings, because we do not find that any information content becomes more effective for incumbents after branded entry. Hence, when a new brand enters, we find for incumbents a decreased effectiveness of both detailing visits with average information content and visits in which sales representatives discuss drug indications and costs.

Third, discussing drug contraindications has a higher effect at the start of the life cycle, compared to later periods, for Crestor (0.0977) and Vytorin (0.4414), but only significantly so for Vytorin. Discussing drug

indications has a significantly higher effect at the beginning of the life cycle for Crestor (0.2860) and Vytorin (0.3267). Discussing drug costs has a significantly lower effect at the beginning of the life cycle for Crestor (−0.3457) and Vytorin (−0.1806). In the period of Crestor's entry, its main improvement over incumbents was its drug indications (Consumer Reports 2014, Quirk et al. 2003). When Vytorin entered the market, its main improvements over incumbents were its drug contraindications and indications (Martinez 2004, Thomaselli 2004). Hence, we find that it is more effective for branded drugs in the first periods after launch to focus on the drug attributes that clearly differentiate them from incumbent drugs, compared to later periods in the drug life cycle.

Fourth, we find that for all incumbents, the effectiveness of detailing visits with average information content decreases significantly in the first six months after the entry of generic drugs for Pravachol and Zocor, as shown in panel (v) of Table 9. After generic entry, price-sensitive doctors have a cheap alternative that they may prescribe by default, whereas promotion-sensitive doctors may still be responsive to detailing of the branded, patent-protected drugs (Gonzalez et al. 2008). This implies that the market over which branded firms compete becomes smaller after generic entry, which decreases the detailing effectiveness. Discussing drug contraindications and indications has a positive effect for competitors after generic entry (in the case of contraindications, this effect is significant for Lipitor (0.1828) and Crestor (0.1591), and insignificant for Vytorin (0.0412); in the case of indications, the effect is significant for Lipitor (0.2546) and Vytorin (0.1585), and insignificant for Crestor (0.0777)).

In sum, it is effective for branded competitors to focus their sales efforts in the first periods after generic entry on "positive" attributes, i.e., features on which they outperform generics. As such, they can take advantage of the lower perceived therapeutic quality of generics (Ching 2010, Kesselheim et al. 2008, Olsson and Sporrong 2012). This argument is comparable to Steenkamp et al. (2010), who find that although the quality difference between national brands and private labels is small, if there is any, national brands can successfully increase consumers' willingness to pay and widen the perceived quality gap through advertising. Note that our results also show that it is more effective for Vytorin to discuss drug costs after generic entry, which may seem, but is not, inconsistent with this argument. Vytorin is a combination of simvastatin (which lost its patent protection) and ezitimibe (still on patent). After generics for simvastatin entered the market, the price of Vytorin was still lower than the combination of branded ezitimibe and generic simvastatin, which sales representatives could successfully emphasize in their sales conversations as a "positive" attribute.

5.3.2. Heterogeneity Across Doctors. As exemplified by our results above and prior literature, different doctors respond differently to detailing. Our focus on information content begs the question whether doctors show differential sensitivities to information content. Given our focus on branded and generic entry, we investigate next whether doctors differentially respond to different information content components of the incumbent brands in the first six months after competitive entry.

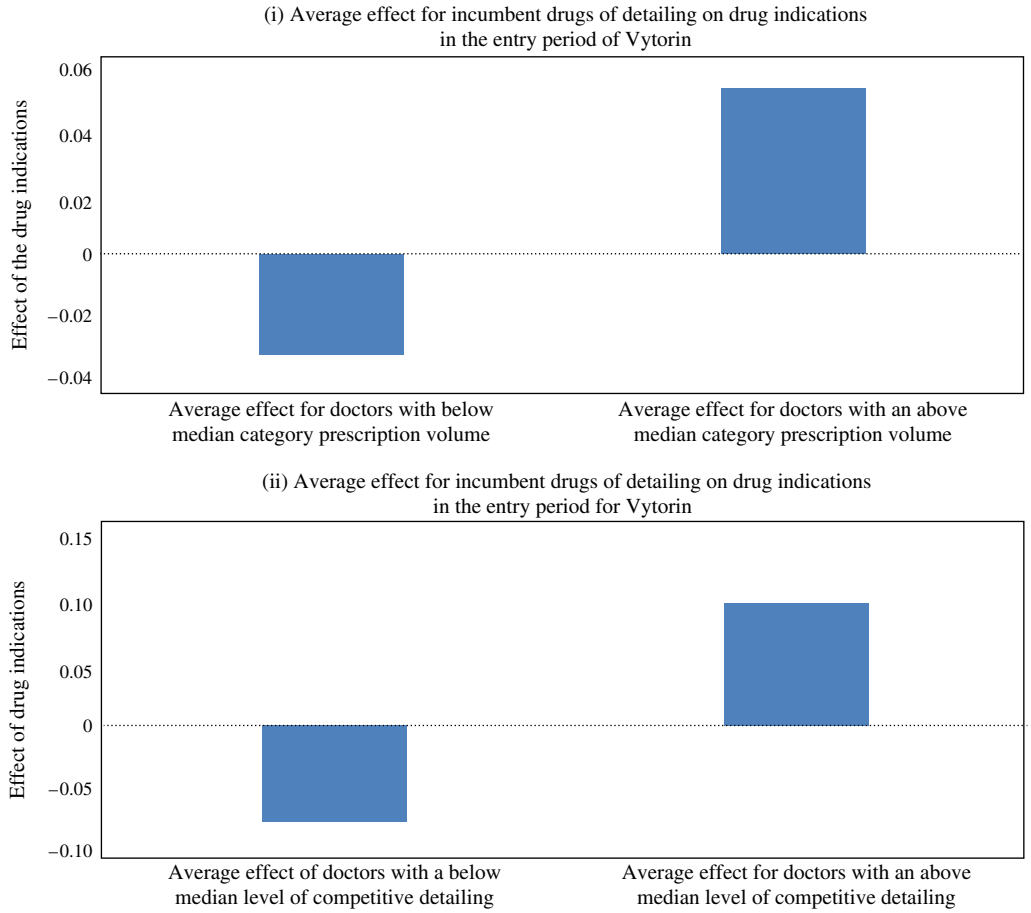
We examine this question by performing a median split on doctors' category prescription volume, the total number of detailing visits they receive, and the sum of the competitive detailing visits they receive. Then, we compute for these three doctor characteristics (i.e., the below and above median group for each variable) the average responsiveness to detailing and information content in the first six months after entry (i.e., α_{2ij}, α_{3ij}, α_{4ij}, α_{6ij}, $\alpha_{7ij}, \ldots, \alpha_{16ij}$) and jointly test across all incumbent brands whether the difference between the two groups for each doctor characteristic is significant by a t-test ($p < 0.05$). We discuss the two most significant findings from this analysis below.

First, upon branded entry, doctors with a high category prescription volume and an above median number of competitive detailing visits are more responsive to details by branded incumbents on drug indications than doctors with low category prescription volume and a below median number of competitive detailing visits. For the entry of Vytorin, panels (i) and (ii) of Figure 1 show the effectiveness of discussing drug indications for prescription volume (the below and above median groups) and competitive detailing (the below and above median groups). The results for the entry of Crestor are comparable and also significant.

Second, upon generic entry, doctors with an above median number of competitive detailing visits are more responsive to details by branded incumbents on drug costs than doctors with a below median number of competitive detailing visits. Figure 2 shows the results for the generic entry for pravastatin and simvastatin for doctors with a below and above median level of competitive detailing.

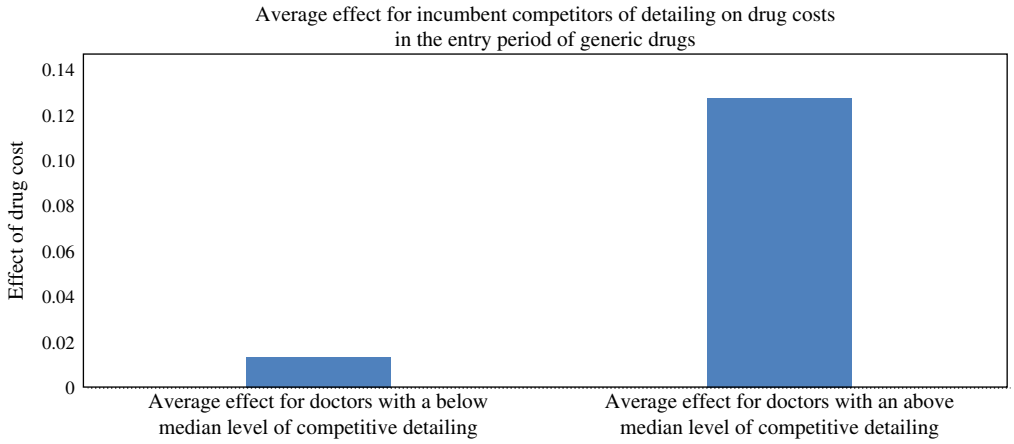
Competitive entry likely increases uncertainty on the information components on which the new entrants positively differentiate themselves from incumbents. In the case of the branded entry of Crestor and Vytorin, both drugs positively differentiated themselves from the incumbent on drug indications. In the case of the generic entry on pravastatin and simvastatin, entrants positively differentiated themselves from the incumbent brands on drug costs. Doctors that write more

Figure 1 (Color online) Doctor Heterogeneity in Response to Information Content Upon Branded Entry



Note. The differences between groups in panels (i) and (ii) are both significant ($p < 0.05$).

Figure 2 (Color online) Doctor Heterogeneity in Response to Information Content Upon Generic Entry



Note. The difference between both groups is significant ($p < 0.05$).

prescriptions and receive more competing details are more time constrained. Therefore, their attention will be more selectively focused on the information components for which uncertainty has increased, thereby learning more efficiently (Hullinger et al. 2014), compared to doctors that write fewer prescriptions and receive less competitive detailing visits.

5.3.3. Results for Control Variables. Panel (vi) of Table 9 shows that prescriptions of the older drugs (Pravachol, Zocor, and Lipitor) follow a negative trend, whereas prescriptions of the newer drugs (Crestor and Vytorin) follow a positive trend. The competitive detailing effects are mixed. Nine out of 20 competitive detailing effects are insignificant, six are

significantly negative, and the remaining five are significantly positive. As is common in pharmaceutical markets, competition may have both market stealing and expansion effects (Dave 2013, Venkataraman and Stremersch 2007).

The main effects for the entry of Crestor and Vytorin (i.e., the effect without the presence of detailing) show that the entry of Crestor decreased prescriptions for Pravachol (−0.4222) and Zocor (−0.1773), but increased prescriptions for Lipitor (0.1263). Zocor's prescriptions decreased after the entry of Vytorin (−0.1396), whereas Crestor's prescriptions increased after the entry of Vytorin (0.2686). Prescriptions for Crestor (−0.7232) and Vytorin (−0.5483) are significantly lower in the first six months of their life cycles, compared to later in their life cycles.

The entry of generics for simvastatin and pravastatin had a significant positive effect on the incumbents Lipitor, Crestor, and Vytorin and a significant negative effect on Pravachol (−2.3536) and Zocor (−0.6359). The positive effects of generic entry on the incumbent brands is driven by between-molecule switching. Given that the promotion of Pravachol and Zocor ended, promotion-sensitive doctors may switch to other molecules, still under patent protection, that are still heavily promoted (Gonzalez et al. 2008). Finally, the monthly dummies for the release of the initial results of the ENHANCE study for Vytorin are all significant.

5.4. Alternative Models

We use the WAIC to compare the in-sample performance of our model against a model in which we ignore information content. The WAIC for our main model is 6,616,219, whereas the WAIC for the model in which we ignore the information content altogether is 6,624,736. Based on the Akaike weights, we find that the probability that the model with information content fits the data best is equal to one (and the probability that the model without information content fits the data best is $<1 \times 10^{-30}$). Thus, it is important to account for information content. We can now also compare the effects of detailing visits in a model that includes information content, compared to a model without information content. For comparison purposes, we report the elasticities resulting from both models. When controlling for information content, we find a short-term detailing elasticity of 0.013 and a long-term detailing elasticity of 0.029. Note that these elasticities are averaged across brands, based on all periods without an entry event, and based on all doctors that received at least one detailing visit during the sample period. The short-term elasticity for the model without information content is 0.018, and the long-term elasticity is 0.044. The higher elasticities in the latter model are caused by the absence of the explanatory variables capturing the amount of drug contraindications, indications, and costs discussed in each sales call.

We also find that the model that includes information content has a better out-of-sample performance than the model without information content. When we calibrate the model without the last six months of the data set and subsequently forecast these last six months, we find that the MAPE for the model without information content is 1.016 times the MAPE for the model with information content.

Our model also outperforms models with controls for serial correlation and with other control variables in the various equations (such as alternative trend terms). We also estimated a model in which we allow for differential carryover effects for detailing and information content via a goodwill stock formulation (a multiple distributed lag model), and we found substantively similar results.

5.5. Firms' Control Over Information Content in Sales Calls: A Survey

A sales call is a two-way conversation, which raises questions of the extent to which the sales representative controls the conversation with the doctor and the extent to which sales representatives can be trained by the firm on the information content they should share with doctors. The literature contains evidence that firms extensively train their sales forces over time to control the content of sales conversations (see Waxman 2005 for details from the documents on sales force training by Merck & Co. submitted to the Government Reform Committee after the Vioxx withdrawal in 2004). We decided in the context of this study to survey both doctors and pharmaceutical sales managers on who steers the conversation and controls the information content exchanged.

We surveyed 20 U.S. doctors with more than 10 years of practice. We asked them how much control the sales representative and the doctor have over the content of a sales call. The results show that on a scale from 0 to 100%, doctors indicate that the sales representative leads the sales conversation 70% of the time, on average. On a scale from 0 to 100, doctors perceive the sales representatives to be highly trained (78 out of 100) on the specific drug attributes they discuss during a sales conversation.

We also interviewed 15 pharmaceutical sales managers with at least two years of experience in pharmaceutical sales. Seventy-seven percent of the sales managers agree that sales representatives steer the information discussed in a sales call. On a scale from 0 to 100%, 57% of drug-related content in the sales conversation is initiated by the sales representative. The sales managers also confirmed that when a new brand enters the market or an existing brand loses patent

protection, they update their sales representatives on the messaging strategy by retraining them, monitoring sales conversations, and updating their visual aids (e.g., on their iPads). Hence, based on these surveys and interviews in a relatively small sample, we find that (1) the sales representative has more influence over the information content in the sales conversation than the doctor, and (2) firms develop messaging strategies and train their sales representatives on the information content they should discuss with doctors.

6. Implications and Limitations

Our study has several implications for academics and management practice. We find that a prescription response model with information content explains and predicts prescriptions better than a model without information content. The model we introduce and the evidence we provide on the role of information content is useful to analysts. For instance, firms such as IMS Health can commercially leverage the panel data used in this paper. Our model provides evidence to their pharmaceutical clients that the monitoring of information content in (own and competing) detailing visits is valuable in explaining detailing responsiveness. Analysts can adopt our model in the delivery of such services. Internal analysts of pharmaceutical firms could also find the modeling framework proposed useful in the mining of their own data. For instance, it would allow the inclusion of information content in their own prescription response models to determine their return on investment on detailing and information content across doctors, sales representatives, or sales territories.

Our findings may also be thought provoking for pharmaceutical marketers and sales managers. Although pharmaceutical firms have significant control over information content in detailing visits (as shown in our survey), their observed responses to competitive entry (Table 4) do not always align well with the response coefficients we estimated (Table 9). For instance, in the first six months after generic entry, it is more effective for branded competitors to discuss drug contraindications and indications than in other periods. By contrast, Table 4 (and also Tables 6 and 7) shows that firms actually discuss this information content somewhat less often in the first six months after generic entry.

Our model also allows us to compare the effectiveness of the different information content components, which can inform messaging strategy. For instance, our survey shows that firms adjust their messaging strategy in response to a significant event, such as a branded or generic entry. We can use our results in Table 9 to determine what information content is most effective to discuss in the first periods after branded or generic entry. As an illustration, we can compute the cumulative effect of a detailing visit for Lipitor on drug indications in the first six months after generic entry as follows: $(\alpha_{1ij} + \alpha_{9ij} + \alpha_{4ij} + \alpha_{12ij})/(1 - \alpha_{21ij})$.[7] Based on Table 9, this equals 0.7126 $(= (0.3319 - 0.2203 + 0.1044 + 0.2546)/(1 - 0.3396))$. This effect is 1.44 times higher than discussing drug contraindications, 2.86 times higher than discussing drug costs, and 4.22 times higher than only discussing average content during the same period.

In addition, it can be valuable for firms to study the responsiveness to detailing and information content at the doctor level. We find that it is more effective for sales representatives of the incumbents to discuss the information content with which the branded and generic entrants differentiate themselves from the incumbents with more active doctors, compared to less active doctors. Therefore, firms can benefit from targeting message content at the doctor level, especially in the first periods after branded or generic entry.

Befitting earlier findings on detailing effectiveness over the life cycle (e.g., Narayanan et al. 2005), we find that the effectiveness of the number of details with average information content is highest during the first six months after launch. We also find that in the first six months after launch, it is most effective to emphasize the new drug's superior attributes in the sales call. Therefore, it is profitable for pharmaceutical firms to courageously scale their sales efforts in the initial periods after approval.

This study also yields future research opportunities. First, extensions to other therapeutic categories and industries would enable researchers to examine related questions. For instance, to what extent do sales representatives in the automotive industry exaggerate certain product features beyond the product's real performance (e.g., mileage)? To what extent do pharmaceutical sales representatives communicate good news from clinical studies more than bad news? To what extent do firms align content across different media (e.g., for pharmaceuticals, detailing to doctors and advertising to patients), and how effective is such integrated communication?

Second, models aimed at optimizing information content in sales calls over time would be a natural next step, as we show that information content matters and its effect changes with events occurring in the category. Equally interesting would be to specify a Bayesian learning model to capture how doctors learn at the drug attribute or component level (Narayanan et al. 2005). If such models exploit the

[7] For illustrative purposes, we assume that the component loading increases by one in our calculations, which is a reasonable assumption given our data.

heterogeneity that we have established across doctors in their response to information content, they can provide powerful targeted sales messaging analytics.

Third, we do not observe in our data who initiated the conversation about a specific attribute. Such data could yield most valuable inquiries. For instance, does information content initiated by the sales representative have a different impact on customer behavior than information content initiated by the customer? Research by Camacho et al. (2014) on the information exchange between doctor and patient, at the patient's or doctor's initiative, and its differential effects on patient empowerment seems to indicate that this may be the case.

Fourth, we did not examine the entry timing of new branded drugs, and treated it as exogenous. Firms have some control over when to launch their drug, but also face uncertainty on the length of the drug development and FDA approval process. Examining the entry timing of branded drugs may reveal valuable insights on how entry timing influences the effectiveness of detailing and information content. Such an examination may be especially interesting for seasonal drugs (such as antihistamines).

Fifth, we used a 6-month dummy to identify the generic entry period. Although we documented the appropriateness of the 6-month period, compared to a 3-month or 12-month period, we feel there is opportunity for future research on the dynamics of generic substitution at a more granular level. There are interesting dynamics, such as the possibility of a 180-day generic exclusivity, increasing number of generic manufacturers, and interfirm agreements on active ingredient supply or market exclusivity, which were outside the scope of the present article, but certainly deserve more scholarly attention.

In sum, we hope that this research triggers the interest of researchers and managers such that marketers enrich their understanding about information content in sales calls.

Supplemental Material

Supplemental material to this paper is available at https://doi.org/10.1287/mksc.2015.0971.

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