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Understanding Responses to Contradictory Information About Products

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Although prior literature has examined reactions to drastic negative news, we examine the situation in which decision makers receive contradictory information about products and they have to decide whether to persist with or abandon product usage. We investigate physician reactions to conflicting information concerning the cardiovascular risk of Avandia, a diabetes drug. We examine how beliefs about both drug *effectiveness* and drug *safety* are updated and speculate that experience, expertise, and self-efficacy impact how such information is integrated with current quality beliefs. Unlike previous Bayesian learning models, we consider that some signals, such as positive and negative news releases and the firm's marketing effort, may be biased in that they provide an opinionated point of view. The results show interesting differences in how physician types (specialists, hospital-based primary care physicians, heavy and light prescribers) update their beliefs and the information sources they use to do so. We find evidence that safety issues about Avandia resulted in spillover concern to close competitor Actos. The results have implication for determining who should be targeted and what vehicles should be used if a firm is faced with a situation where consumers are in a quandary because of receiving conflicting messages.

Key words: contradictory information; learning models; pharmaceutical markets; endogeneity; hierarchical Bayes models
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1. Introduction

Because consumers are increasingly confronted with negative news about products, how they integrate this new information with current beliefs is of vital interest to managers and policy makers. Previous research (e.g., Dawar and Pillutla 2000) has largely considered situations where the nature of the negative information is unequivocal. In cases of product contamination (e.g., milk tainted with melamine, peanuts causing salmonella) or drastic product dysfunction (e.g., products associated with asbestos, lead poisoning, or choking hazards), the content of the information is categorical and the implications clearly evident. In these situations, an established pattern of consumer reaction is for all consumers to desist from further product usage and then gradually resume product consumption after the perceived danger dissipates (e.g., Cleeren et al. 2008). In contrast to earlier literature, our focus is on situations where the content and implications of the new negative information are not clear cut.

Decision makers frequently encounter new negative facts about products where the connotation of the information does not decidedly suggest product abandonment for all people. Consider that between January 1, 2001, and January 31, 2008, the U.S. Consumer Product Safety Commission (CPSC) issued 4,503 product safety alerts that did not include product recalls. In 2009, it issued 497 such alerts. The safety alerts involved a wide variety of products and several sports and recreation related activities. For example, one alert warned consumers of severe hand injuries when using a snow thrower (CPSC Release 92-0470). Another warned of severe burns from hair curling irons (CPSC Document 5029). Examples concerning activities include possible severe hazards related to exercising on trampolines, rollerblading, and riding on all-terrain vehicles (see http://www.cpsc.gov/ for more examples).

Often, the quandary caused by the negative information is not only because of its uncertain import but also because the information itself is contradictory. Such instances include the use of cycle helmets,

zinc ingredients for cold remedies, and several pharmaceutical drugs. For example, examining safety for cyclists, one of the early studies claimed that helmets reduce head injuries by 85% and brain injuries by 88% (Thompson et al. 1989). In another study published a little earlier, Rodgers (1988), using a sample of eight million injuries, not only found no evidence of decreased injuries but also found a significant positive correlation between fatalities and helmet use. There are numerous follow-up studies supporting helmet effectiveness as well as ineffectiveness.[1] UK's National Cyclists' Organisation, CTC, concluded that "the evidence currently available is complex and full of contradictions, providing at least as much support for those who are sceptical as for those who swear by them." Interestingly, the U.S. CPSC recommends helmet usage, whereas the CTC does not.

In this paper, we investigate how decision makers respond to new contradictory information about an established product and explain the heterogeneity in responses. We examine how decision makers update product quality beliefs based on the information releases and their subsequent decisions on whether to persist with or abandon the product. We study physician reactions to the release of information on Avandia, one of the leading drugs for treatment of type II diabetes. The controversy began after the *New England Journal of Medicine* (*NEJM*) published a meta-analysis (Nissen and Wolsky 2007) warning of increased cardiovascular risk associated with Avandia. Starting with an editorial in the same issue of *NEJM*, which criticized the study's methodology on several grounds and advocated more research (Psaty and Furberg 2007), other releases of information by the U.S. Food and Drug Administration (FDA), medical journals, and the media either counselled that the product be discarded or recommended continuing usage. We examine physicians' choices of prescriptions (including both new prescriptions and refills) with the advent of the contradictory recommendations using a physician–patient–level longitudinal prescription data set in the diabetes category starting 17 months before the safety announcement to 5 months after the first Avandia warning.

1.1. Model Overview

Much of the research on the impact of negative information has followed the experimental paradigm (e.g., Ahluwalia et al. 2000), with the recent exceptions of Cleeren et al. (2008) and van Heerde et al. (2007). The only empirical examination of individual level differences is Cleeren et al. (2008). The main finding on responses to negative information in the experimental literature and confirmed empirically is that favorable brand attitudes or brand familiarity provides some cushion to negative information (e.g., Ahluwalia 2002).

Unlike previous research examining the effects of negative information, we propose a multivariate hierarchical Bayes model of prescription choices within the Bayesian learning framework. Physicians are conceptualized to update their product quality beliefs on receipt of the contradictory information and several other information signals. The learning is further categorized as general belief updating about both the effectiveness of the drug and drug safety. Prior research views prescription behavior as an outcome of learning that takes place from feedback signals (detailing, patient feedback) that are unbiased but noisy signals of the drugs' quality. However, such a methodology cannot be directly translated to this research problem for two reasons. First, classical Bayesian models only allow for monotonic changes in the quality perceptions of the physicians and thereby prescription behavior, which flatten out. The key difference in the Avandia problem is that the existing approaches can explain physician behavior only prior to the contradictory news release. A different approach is needed to explain any sudden drastic changes in quality perceptions that could occur after the release of fundamentally new information.

Second, physicians learn about drug effectiveness and safety from patient feedback, marketing mix variables of sampling and detailing, and public information release such as medical updates and FDA announcements. A methodological issue is modeling the impact of positive and negative media news and detailing (regarding the drug safety) on the physicians' quality beliefs. In this context, each of these provides contradictory information to the physicians, which cannot be accommodated in standard Bayesian models because in such models, all information is assumed to be unbiased. However, media reports were biased in that some specifically counseled readers to stop taking Avandia, whereas others took the view that the jury was still out and recommended that the readers consult their physicians. Clearly, detailing by Avandia after the news releases was also biased. Following the approach of Mehta et al. (2008), we allow for three sources of information about the drug's safety (positive and negative media news and detailing) to be biased, whereas the physicians have different beliefs about the extent of information bias for different drugs. As a result, the physicians suspect the credibility of the information on some brands versus the others. Naturally, the more suspect the information, the lower its impact in the updating process. Also, we allow different types of physicians to have

[1] Bicycle Research Foundation. Cycle helmets—An overview. Accessed February 2009, http://www.cyclehelmets.org/1139.html.

different learning processes on drug effectiveness and safety. These differences account for why physicians reacted differently to the news.

1.2. Main Findings and Contributions

We find that compared to primary care physicians (PCPs), who have less overall experiences in the diabetes category, lower expertise, and less self-efficacy, physicians with more overall diabetes experiences (specialists) tend to be less likely affected by the contradictory information release. Also, within PCPs, physicians who prescribe more heavily in the diabetes category and those who are affiliated with hospitals tend to have more muted reactions. Whereas specialists and hospital-based PCPs update their perceptions about drug safety based only on patient feedback and negative news, the office-based PCPs are swayed by any information source (both positive and negative) and are also more responsive to marketing effort. Based on the estimates of the proposed model, we conduct several counterfactual policy experiments using simulations, determining that customizing the marketing efforts of the focal brand can increase its revenue by 46.99% overall and by 148.74% after the initial news.

Our main contributions are these: (i) To the best of our knowledge, this is the first study that empirically examines heterogeneous reactions to contradictory information. (ii) We depart from extant reaction to negative information literature by using a Bayesian learning framework to examine how the new information is integrated with current beliefs, and we allow asymmetric impact of positive and negative news on decision makers' learning. (iii) Methodologically, we differ from earlier Bayesian learning models by allowing various information sources to be biased and multiple endogenous marketing variables to be correlated. (iv) We allow various types of decision makers to update quality beliefs with different learning processes.

We next present the potential reasons why physician responses may differ and the pertinent industry background and data information. We then develop our econometric model and finally discuss the results and their implications.

2. Differences in Responses

We examine differences in reactions between physician types. We anticipate that different types of physicians will react differently to the new information. There are a number of reasons why responses may differ. Because of their education and experience in diabetes treatment, specialists have greater overall expertise in dealing with diabetes and are also likely to have higher self-efficacy (e.g., Bandura 1982). Also, specialists could be dealing with patients with more severe diabetes (though it is common for many PCPs to also manage diabetics for long periods). We therefore anticipate that specialists will react less to contradictory information than would PCPs. Among PCPs, there are differences between those who are hospital-based and those who have office-based practices. Compared with private office-based practice, hospitals are characterized by better resources and high levels of peer interaction (e.g., Hoff et al. 2001). Hospital-based PCPs are therefore likely to better discern the nature of the contradictory information. Experience with the disease improves the ability to analyze the requirements posed by the task, deduce causality between actions and outcomes, and better assess resources and constraints that bear upon performance (Gist and Mitchell 1992). We therefore also examine whether PCPs who prescribe more in the diabetes category (heavy prescribers) react less to the inconclusive negative information than do their counterparts who prescribe diabetes drugs less frequently (light prescribers).

3. Background Information

Avandia, introduced by GlaxoSmithKline in June 1999, is an oral medicine to treat type II diabetes. Type II diabetes is treated by a wide variety of physician specialties including PCPs, endocrinologists, and diabetologists (specialists). PCPs, which cover specialties such as general practice, family practice, and internal medicine, are generalists. Therefore, unlike specialists, they possess less knowledge and experience in treating diabetes. There is heterogeneity in PCPs' knowledge about and approach to treating diabetes, with some PCPs referring patients to specialists early and others managing them for a long time.

Typically, treatment begins with oral medications until insulin becomes necessary. Oral medications include Actos and Avandia and generic products such as metformin and sulphonylureas. Both Avandia and Actos belong to a class called thiazolidinedione. Actos, an Eli Lilly product, was introduced one month after Avandia in July 1999. Avandia and Actos can be used as monotherapy or in combination with other antidiabetic medications such as metformin. Because the other classes in the oral diabetes drug category only represent a small portion of diabetes treatment, we aggregate them together as "Others."

3.1. Avandia and Sequence of Events

A successful product, Avandia's gross sales reached approximately $2.2 billion in 2006 (McGuire 2007). On May 21, 2007, *NEJM* published an article online based on a meta-analysis of 42 trials (Nissen and Wolski 2007), suggesting that Avandia may be associated with increased risks of heart attack and death from cardiovascular diseases. Acknowledging the study's strength and merits, the editorial in the same issue

also pointed out several serious methodological limitations of the study, emphasizing that the authors also had mentioned the "fragility of their findings" (Psaty and Furberg 2007, p. 2522). Because the results of *NEJM* article were widely publicized by national media, including *USA Today*, the *Wall Street Journal*, and the *New York Times*, Avandia's safety concern quickly became well known among physicians as well as the general public. Although some physicians believed and supported the conclusions of this study, several methodological concerns (e.g., many trials were not peer reviewed, six trials with no cardiac problems were omitted, and the largest did not even include patients with diabetes) were echoed by other experts (U.S. House of Representatives 2007).

Because of the contradictory and inconclusive nature of this study, the reactions of authorities and medical associations were cautionary. On the same day of publication, the American College of Cardiology, the American Diabetes Association, and the American Heart Association issued a statement saying that although "this study deserves serious thought and follow-up. As estimated here, the overall level of the risk associated with rosiglitazone [Avandia] appears to be small," adding that "patients should not stop taking any prescribed medications without first discussing the issue with their health care provider. Further research will be needed in this area to provide conclusive evidence" (American Diabetes Association 2007).

Later that day, as a precaution, the FDA issued a safety alert on Avandia. Unlike other drugs that are sometimes asked to withdraw (e.g., Palladone, Zelnorm, Vioxx), the FDA recommended that both Actos and Avandia add a black-box warning indicating the safety concern. On July 30, the FDA advisory committee composed of a panel of experts, voted 22 to 1 recommending that Avandia remain on the market. Based on the recommendations from the expert panel, on August 14, the FDA issued an updated label with a black-box warning for both Avandia and Actos, allowing both products to remain on the market.

On October 18, after a review of Avandia's benefits and risks, the European Medicines Agency (2007) issued a press release, confirming a "positive benefit-risk balance" for Avandia and concluding that the "benefits of these antidiabetic medicines continue to outweigh their risks in the approved indications." Meanwhile, the sales of Avandia declined.

3.2. Data Description

We use a data set titled Anonymous Patient-Level Data provided by IMS Health, a leading pharmaceutical market research firm. The data set contains individual physicians' prescription choices over time at the patient level. For each individual prescription, we observe information on (i) whether it is new prescription or a refill; (ii) the prescribing physician's information such as specialty and location (office- or hospital-based, or Others); (iii) patient characteristics including gender, age, and insurance coverage (Medicaid, third-party insurance, or cash); and (iv) the prescription characteristics, consisting of the drug name, units of the medication dispensed, drug strength, and prescription date. We combine these data with physician-level promotional information, also provided by IMS Health, which provides the extent of detailing and sampling for each brand at the physician level per month.

Our study focuses during the time period between January 1, 2006, and October 26, 2007. Data made available to us consist of a random sample of 1,500 physicians who treat a total of 10,392 patients in the analysis period. Of these 1,500 physicians, 46 are specialists, 37 are hospital-based PCPs, 1,079 are office-based PCPs, and 338 are other specialties. The proportion of specialists in our data set is representative of the true physician population, i.e., 2% to 3% of total physicians who treat diabetes are specialists. On average, specialists, hospital-based PCPs, office-based PCPs, and other specialities treat 20.13, 7.68, 7.19, and 4.22 patients, respectively. We use 1,000 randomly selected physicians for the estimation and the remaining 500 physicians as the holdout.

The data consist of all oral diabetes drugs. We do not include injectable drugs such as Symlin, Byetta, and insulin because they are usually the last resort and therefore are unaffected by the Avandia news. Diabetes patients are required to follow up with physicians with regular visits during which blood sugar levels and other outcomes are measured. Physicians frequently adjust prescriptions (including adding on/switching to a new brand or changing dosage). Therefore, our analysis does not differentiate between refilled and new prescriptions.

Figure 1 illustrates prescription shares for each drug over time. As can be seen, the contradictory

Figure 1 Different Drug's Prescription Share Over Time

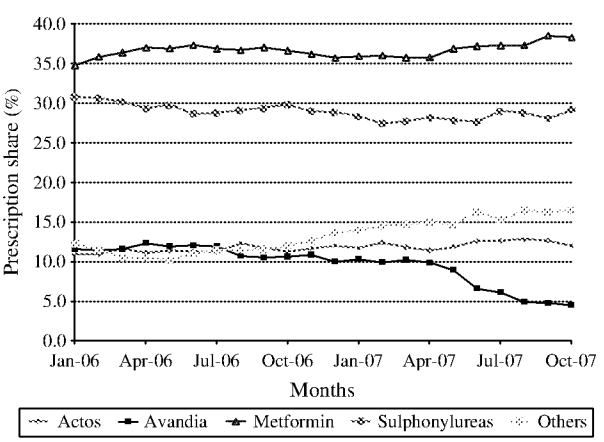
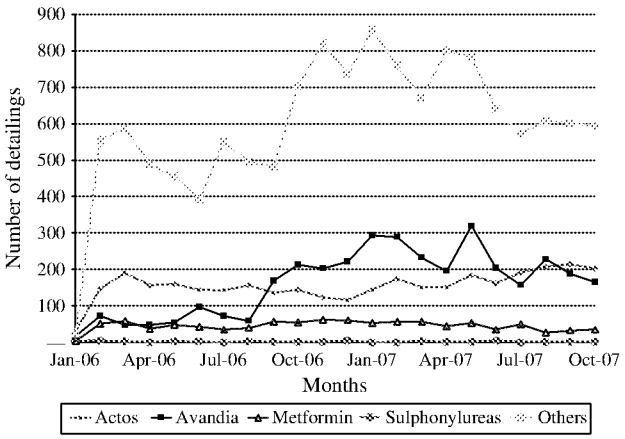


Figure 2 Detailing Activities of Different Drugs Over Time



information has a large negative impact on the market share of Avandia. Meformin and Others benefit, whereas Actos temporarily gains share. Figure 2 shows that Avandia decreased detailing, and close competitor Actos increased it. Table 1 provides a breakup of Avandia and Actos marketing expenditures to physician types before and after the news. Overall, Avandia decreased its detailing (−29.3%) and sampling efforts (−33.9%) after the event. Furthermore, we observe that Avandia reduced detailing for office-based PCPs and other physicians after the event, maintained it for specialists, but increased it for hospital-based PCPs.[2] Sampling is cut across the board but increased for hospital-based PCPs. A closer look at the prescription frequency for different physicians reveals that different doctors tend to respond differently to the news. With the advent of the information, specialists tend to switch to other drugs; hospital-based PCPs, to Actos; and office-based PCPs, to Actos, metformin, and "Others." We discuss details of the responses in §§4.1 and 6.

Descriptive statistics of key variables are listed in Table W1 of Appendix C in the electronic companion, available as part of the online version that can be found at http://mktsci.pubs.informs.org/. Besides obvious variables such as the patient's gender, age, and insurance coverage, other patient characteristics such as disease severity play an important role in physicians' prescription decisions. We use the average strength of patients' current medications as a surrogate of disease severity. Drug strength is measured by the average potency of all past prescriptions, with higher levels reflecting greater disease severity.

[2] The increase in hospital-based PCPs may be explained by the accessibility of the physicians. Hospital-based doctors are widely perceived by sales representatives to be extremely difficult to access because of their workload demands. However, because of the high exposure of the *NEJM* article, we speculate that the hospital-based PCPs became curious about Avandia and were more inclined to meet the sales representatives.

National media followed up on the *NEJM* article with coverage about the main results. This information also likely influenced physicians' learning about drug safety. We therefore collected all major print coverage between May 21, 2007, and October 26, 2007. Information sources include national newspapers with high circulation (e.g., the *Wall Street Journal*, the *New York Times*, *USA Today*) as well as credible sources such as FDA and European Medicines Agency websites. Every newspaper report was "biased" because it also provided counsel on whether patients ought to abstain from taking Avandia. If the newspaper report explicitly advocated that patients should stop using Avandia, we considered it as "negative" information. If the report was agnostic, concluding that more research was necessary or recommending that patients discuss it with their physicians, we considered it as "positive" information. Of the 112 news reports, 65 are categorized as negative and the remaining 47 as positive. Because diabetes is an extreme disease, we consider that the physician has the final say on the prescription decision. However, we also account for the patient's influence on the physician's prescription choices.

4. Model Setup

Similar to previous literature (e.g., Chintagunta et al. 2009, Narayanan and Manchanda 2009), we assume that the physician is the sole decision maker for prescription decisions. We also assume away the potential information and incentive issues present in the doctor–patient relationship. These are reasonable assumptions given the severe nature of the disease. Because the physician's prescription choices are not mutually exclusive, we assume that the physician will prescribe a particular drug as long as the utility from the drug is greater than a threshold (normalized to zero). Thus, we use a multivariate probit model to capture physicians' behavior of both new and refill prescriptions. We also compute the sample transition matrix of the five brands from the data and find no prescribing order among these brands.

The physician's prescription decision depends on, among other factors, (1) the physician's perception of drug effectiveness and drug safety as well as his or her risk attitude, (2) marketing contacts of the pharmaceutical firms, (3) the patient's influence including the patient's feedback and his or her condition and characteristics, (4) out-of-pocket cost for the patient, and (5) contradictory information releases on Avandia. This is consistent with the earlier findings in the pharmaceutical marketing literature (Chan et al. 2010, Chintagunta et al. 2009, Narayanan et al. 2005).

4.1. Preliminary Analysis

We first ran a simple multivariate probit model to see how different physicians' prescriptions change with

Table 1 Avandia and Actos Marketing Expenditure Changes After Avandia News

Brands	Total percentage change	Physician types: Specialists (%)	Hospital-based PCPs (%)	Office-based PCPs (%)	Other physicians (%)
Actos					
Detailing	21.47	17.14	0.00	19.94	35.71
Sampling	−2.49	−42.11	−37.50	−6.96	49.45
Avandia					
Detailing	−29.76	−3.70	25.00	−31.49	−35.00
Sampling	−33.93	−81.82	131.25	−35.55	−21.40

Note. Number indicates five months before and after the news.

the onset of the contradictory information. In the utility function of this simple model, aside from variables such as detailing, sampling, and patient characteristics, we also create a dummy variable to represent the first news release (the May 2007 publication of the *NEJM* article on Avandia). Furthermore, we incorporate physician heterogeneity in the response parameters. The results are presented in Tables 2–5. Table 2 shows that patient feedback,[3] detailing, and sampling all have positive impact on the physicians' prescription decisions. The parameter estimate for the interaction between detailing and sampling is negative, emphasizing the importance of careful and selective multiple marketing activities. It is apparent from Table 3 that the first news release on Avandia has a negative impact on Avandia and Actos prescriptions but a positive effect on other drugs. Table 4 shows that specialists and hospital-based PCPs are more responsive to patient feedback, whereas office-based PCPs are more receptive to detailing. From Table 5, we observe that different types of physicians respond to the Avandia news differently. Given the advent of the first news release, the response of specialists and hospital-based PCPs is less negative than is the response of office-based PCPs on Avandia prescriptions. Compared with specialists and hospital-based PCPs, office-based PCPs are more likely to prescribe metformin, a drug that has been on the market for long time. Next, we discuss our proposed model.

4.2. Utility Function

We assume that for physician i, patient k, and brand j at prescription occasion t, the utility function can be written as (Chan et al. 2010, Ching 2010, Erdem and Keane 1996)

$$U_{ijkt} = W_i(\tilde{Q}_{ijkt} + \tilde{q}_{ijkt}) - W_i r_i \cdot (\tilde{Q}_{ijkt} + \tilde{q}_{ijkt})^2 + \boldsymbol{\gamma}_i' \hat{\mathbf{X}}_{ijkt} + \boldsymbol{\beta}_{ij}' \mathbf{X}_{ikt} + \varepsilon_{ijkt}, \quad (1)$$

[3] Because patient feedback is not directly observed, we use the number of patient visits at the brand level to approximate patient feedback. A detailed discussion is in §4.2.

where $\tilde{Q}_{ijkt}$ is the physician's perceived drug effectiveness of brand j for patient k at time t, and $\tilde{q}_{ijkt}$ represents physician i's perceived drug safety of brand j for patient k at time t. We allow the physician to learn about both drug effectiveness and drug safety (a detailed discussion is in §4.4). W_i is the weight attached to the perceived effectiveness and safety for physician i; r_i is the physician's risk coefficient on $\tilde{Q}_{ijkt}$ and $\tilde{q}_{ijkt}$. Note that although physicians learn about drug effectiveness throughout the data period with updated $\tilde{Q}_{ijkt}$ at each prescription occasion, their learning on drug safety starts only after the first news release on Avandia in May 2007, and hence $\tilde{q}_{ijkt}$ will be the physician's prior belief with any updating beginning only after the first news release. Also, ε_{ijkt} represents the error term, which we assume follows a multivariate normal distribution with $\varepsilon_{ijkt} \sim \text{MVN}(0, \Sigma)$.

The brand-specific vector $\hat{\mathbf{X}}_{ijkt}$ contains marketing contacts of pharmaceutical companies and the patients' feedback. Marketing contacts include the cumulative number of detailing contacts and drug samples for each brand. We take log transformation of these variables to capture their potential nonlinear effects (we add one to the value to avoid the log of zero problem when applicable; see Dong et al. 2009). We set $\boldsymbol{\gamma}_i$ as the coefficients of the covariates in the vectors $\hat{\mathbf{X}}_{ijkt}$. Previous studies (e.g., Narayanan and Manchanda 2009) have shown that marketing contacts can have both an informative effect (through the learning process) and a persuasive effect (any prestige, image, or reminder effects) on the utility of the

Table 2 Estimates for the Simple Multivariate Probit Model—Nonbrand-Specific Variables

Variable	Estimate	Std. dev.
Log of cumulative patient visits	**0.873**	**0.016**
Log of cumulative detailing	**2.276**	**0.117**
Log of cumulative sampling	**1.009**	**0.150**
Log of cumulative detailing ∗ *Log of cumulative sampling*	**−0.516**	**0.073**

Note. Bold denotes significant estimates (i.e., zero does not lie in the 95% posterior probability interval of the estimate.

Table 3 Estimates for the Simple Multivariate Probit Model—Brand-Specific Variables

Variable	Actos	Avandia	Metformin	Sulphonylureas	Others
Intercept	**−0.676**	**−0.321**	**−1.235**	**−0.689**	**−1.708**
	(**0.050**)	(**0.014**)	(**0.023**)	(**0.027**)	(**0.076**)
Patient age	**−0.044**	**−0.047**	**−0.025**	**0.005**	**−0.042**
	(**0.001**)	(**0.001**)	(**0.002**)	(**0.001**)	(**0.002**)
Patient gender—Male	**0.104**	**−0.151**	**−0.088**	−0.003	**0.127**
	(**0.027**)	(**0.026**)	(**0.017**)	(0.022)	(**0.032**)
Avg. drug strength	**0.127**	**−0.066**	**0.204**	−0.017	**−0.106**
	(**0.043**)	(**0.027**)	(**0.030**)	(0.024)	(**0.019**)
Payer type—Medicaid	**−0.307**	**−0.350**	**0.140**	**0.339**	**0.202**
	(**0.065**)	(**0.100**)	(**0.023**)	(**0.025**)	(**0.044**)
Payer type—Cash	**−0.020**	**−0.026**	**0.010**	**−0.019**	**−0.014**
	(**0.001**)	(**0.001**)	(**0.001**)	(**0.001**)	(**0.001**)
First news release	**−0.397**	**−1.317**	**0.504**	**0.393**	**0.636**
	(**0.023**)	(**0.024**)	(**0.015**)	(**0.016**)	(**0.025**)

Note. Bold denotes significant estimates (i.e., zero does not lie in the 95% posterior probability interval of the estimate.

physician. Following this literature, we use the coefficients for the marketing contacts (part of $\boldsymbol{\gamma}_i$) to capture the persuasive impact of such marketing effort, whereas the effects of the marketing variables on utility through the learning processes (i.e., through $\tilde{Q}_{ijkt}$ and $\tilde{q}_{ijkt}$) are referred to as the informative effects.

Table 4 Estimates for the Simple Multivariate Probit Model—Heterogeneity Function

Variable	Intercept	Specialists	Office-based PCPs	Hospital-based PCPs	Other doctors
Log of cumulative patient visits	**1.024** (**0.156**)	**0.297** (**0.107**)	**−0.165** (**0.055**)	**0.240** (**0.095**)	−0.080 (0.160)
Log of cumulative detailing	**1.590** (**0.465**)	−0.232 (0.558)	**0.589** (**0.118**)	−0.075 (0.685)	**1.185** (**0.593**)
Log of cumulative sampling	0.903 (0.966)	−0.515 (0.998)	0.007 (0.976)	−0.541 (1.085)	0.569 (0.968)
*Log of cumulative detailing * Log of cumulative sampling*	−0.585 (0.371)	0.188 (0.417)	0.120 (0.377)	0.377 (0.620)	−0.134 (0.411)

Note. Bold denotes significant estimates (i.e., zero does not lie in the 95% posterior probability interval of the estimate.

Table 5 Estimates for the Simple Multivariate Probit Model—Heterogeneity for First News Release

Variable	Intercept	Specialists	Office-based PCPs	Hospital-based PCPs	Other doctors
Actos	**−0.200** (**0.041**)	**−0.164** (**0.072**)	**−0.118** (**0.047**)	−0.171 (0.146)	**−0.453** (**0.066**)
Avandia	**−0.982** (**0.059**)	**0.183** (**0.099**)	**−0.341** (**0.045**)	**0.629** (**0.156**)	**−0.490** (**0.061**)
Metformin	**0.560** (**0.032**)	0.042 (0.072)	**0.053** (**0.023**)	0.021 (0.117)	−0.091 (0.077)
Sulphonylureas	**0.354** (**0.019**)	−0.017 (0.065)	0.041 (0.023)	−0.039 (0.083)	0.049 (0.040)
Others	**1.042** (**0.029**)	**0.351** (**0.081**)	**0.425** (**0.033**)	**−0.699** (**0.171**)	**0.471** (**0.057**)

Note. Bold denotes significant estimates (i.e., zero does not lie in the 95% posterior probability interval of the estimate.

We account for the patient's influence on the physician's prescription decisions in two ways. First, we use the number of patient visits to the physician at the brand level (one covariate in $\hat{\mathbf{X}}_{ijkt}$) to approximate the patient's feedback because we do not observe the exact feedback in the data. This brand-specific proxy is reasonable given that more visits for a particular drug may communicate more information to the physician. Second, we control for the patient's condition and characteristics. The vector $\mathbf{X}_{ikt}$ consists of patient characteristics such as the patient's age, gender, and conditions, which are not brand-specific. We use average drug strength up to the end of time $t-1$ to approximate patient conditions. $\boldsymbol{\beta}_{ij}$ are the coefficients of the covariates in the vector X_{ikt}.

We do not observe the drug prices and how much the patient actually paid. To account for the out-of-pocket cost of the patient, we follow Chan et al. (2010) to use the patient's insurance type (one covariate in X_{ikt}) as a proxy. Because insurance may have different coverage for different drugs, we allow the coefficient of the insurance type to be brand-specific and hence capture this factor. Finally, we incorporate the contradictory information release on Avandia into the physician's learning on drug safety and discuss it in detail in §4.4.

4.3. Endogeneity on Marketing Contacts

Firms frequently have some knowledge about individual physicians' information when making detailing and sampling decisions. To account for potential endogeneity of physician-level detailing and sampling efforts, following Manchanda et al. (2004), we allow these marketing contact decisions to be a function of the physician-specific response parameters of detailing, sampling, and its interaction term in Equation (1). Note that the firm is unlikely to

have knowledge on the response parameters of the physician's perceived drug effectiveness and safety, the patient's influence, and out-of-pocket cost (e.g., Manchanda et al. 2004). Given that the marketing contacts are count data with overdispersion, we assume both detailing and sampling decisions to follow negative binomial distribution with mean D_{ijt} (S_{ijt}) and overdispersion parameter a (b), respectively, as follows:

$$\Pr(D_{ijt}\mid\lambda_{ij}^{D})=\frac{\Gamma(a+D_{ijt})}{\Gamma(a)\Gamma(D_{ijt}+1)}\left(\frac{a}{a+\lambda_{ij}^{D}}\right)^{a}\left(\frac{\lambda_{ij}^{D}}{a+\lambda_{ij}^{D}}\right)^{D_{ijt}},$$
$$\Pr(S_{ijt}\mid\lambda_{ij}^{S})=\frac{\Gamma(b+S_{ijt})}{\Gamma(b)\Gamma(S_{ijt}+1)}\left(\frac{b}{b+\lambda_{ij}^{S}}\right)^{b}\left(\frac{\lambda_{ij}^{S}}{b+\lambda_{ij}^{S}}\right)^{S_{ijt}}. \quad (2)$$

The mean of D_{ijt} or S_{ijt} is a function of three physician-specific coefficients in Equation (1) as

$$\ln(\lambda_{ij}^{D})=\phi_{j0}+\phi_{j1}\gamma_{i1}+\phi_{j2}\gamma_{i2}+\phi_{j3}\gamma_{i3},$$
$$\ln(\lambda_{ij}^{S})=\delta_{j0}+\delta_{j1}\gamma_{i1}+\delta_{j2}\gamma_{i2}+\delta_{j3}\gamma_{i3}, \quad (3)$$

where γ_{i1}, γ_{i2}, and γ_{i3} refer to the physician-specific response parameters of detailing, sampling, and its interaction term, respectively. The brand-specific ϕs and δs capture different firms' knowledge about these response parameters for different drugs.

Because the firm may use the same knowledge on physicians' response parameters to set their detailing and sampling efforts, it is likely that they are correlated. Therefore, we allow pairwise correlation between the ϕs and δs in Equation (3) and assume that it follows a multivariate normal distribution. That is,

$$\begin{pmatrix}\phi_{jl}\\ \delta_{jl}\end{pmatrix}\sim \mathrm{MVN}\left[\begin{pmatrix}\bar{\phi}\\ \bar{\delta}\end{pmatrix},\Psi\right] \quad \text{for } l=0,1,\ldots,3. \quad (4)$$

4.4. Physician Learning About Drug Effectiveness and Safety

Consistent with the literature (Ching 2010, Chintagunta et al. 2009, Erdem and Keane 1996), we assume that when treating patient k, physician i is uncertain about the true "quality" of drug j. We further divide the true drug quality into two dimensions: drug effectiveness (Q_{ij}) and drug safety (q_{ij}). Drug effectiveness represents a drug's overall efficacy and minor side effects. Drug safety indicates a drug's profile that involves major risks and complications. We assume that physician i is uncertain about both components and learns about them in a Bayesian fashion. Physicians learn about drug effectiveness as soon as the product is launched. Most drugs are considered safe because otherwise, they would not be approved by the FDA. Therefore, physicians' priors are that the drug is safe; any learning on drug safety occurs only on new information release (e.g., the *NEJM* article). The identification of these two components of quality is necessary because physicians' learning on drug effectiveness already reaches a stable state before the first information release on Avandia in May 2007, whereas their key learning about drug safety occurs only after. Because all that is known on safety is that the FDA has approved the drug, it is reasonable to assume that physicians' prior belief on the drug safety has zero mean (i.e., one required identification condition) and some variance. We will discuss the identification issues in detail in §4.7.

We consider that physicians learn about drug *effectiveness* based on the information signals from two sources throughout the data period (i.e., before and after the first news release on Avandia): (i) patient feedback via doctor–patient interactions (cumulative number of the patient's visits) and (ii) pharmaceutical firms' detailing contacts. Furthermore, we consider that physicians learn about drug *safety* only after the first information release on Avandia from the following sources: (i) patient feedback after the first news release; (ii) positive and negative public information release on Avandia, including medical journal publications, national news reports, and FDA updates; and (iii) pharmaceutical firms' detailing contacts. To account for potential category-level carryover effect, we allow the information release on Avandia to influence the physician's learning on the drug safety of all the brands. Based on discussions with managers, we do not include sampling as a signal in the learning because its informative role regarding effectiveness and safety is minimal.

As discussed earlier, information releases were contradictory, advocating either that prescriptions be halted or that it was acceptable to continue. Based on the conclusion, we code the news reports as positive or negative. All detailing is naturally considered to be positively biased toward Avandia's safety profile. Unlike prior literature on physician learning that assumes information sources provide unbiased signals, we consider that the physicians recognize that messages are likely to be biased and formally estimate these brand-specific biases, following Mehta et al. (2008). We discuss the details on the perceived biases in the Appendix A of the electronic companion.

To capture the heterogeneity in learning, we divide physicians into four observable groups: specialists, hospital-based PCPs, office-based PCPs, and other doctors (denoted as subscript r).[4] We then allow each of the four physician types to learn both the

[4] Narayanan and Manchanda (2009) allow individual-level learning. As we are primarily interested in explaining the information integration and choice behavior of different types of doctors, we model segment-level heterogeneous learning.

drug effectiveness and safety differently. The detailed learning process is provided in the Appendix A of the electronic companion.

Physicians are assumed to prescribe a particular drug based on the expected utility derived from the drug. Note that physicians fully observe the market disturbance ε_{ijkt} at time t, whereas researchers do not. But physicians are uncertain about the drug effectiveness $\tilde{Q}_{ijkt}$ and safety $\tilde{q}_{ijkt}$ when making prescription decisions. Therefore, we have the following expected utility given the posterior updates at time t:

$$\begin{aligned} E[U_{ijkt}] = {} & W_i \cdot (\bar{Q}_{ijkt} + \bar{q}_{ijkt}) \\ & - W_i r_i \cdot (\bar{Q}^2_{ijkt} + \Omega_{ijkt} + 2\bar{Q}_{ijkt}\bar{q}_{ijkt} + \bar{q}^2_{ijkt} + \Xi_{ijkt}) \\ & + \boldsymbol{\beta}'_{ij}\mathbf{X}_{ikt} + \boldsymbol{\gamma}'_i\hat{\mathbf{X}}_{ijkt} + \varepsilon_{ijkt}, \end{aligned} \tag{5}$$

where the exact expressions of $\bar{Q}_{ijkt}$ and $\bar{q}_{ijkt}$ are given in the Appendix A of the electronic companion.

We let the prescription decision variables Y_{ijkt} be determined by

$$Y_{ijkt} = \begin{cases} 1 & \text{if } E[U_{ijkt}] > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

Thus, physicians choose a drug with the positive expected utility. Note that the realizations of the five signals (i.e., sample means A_{ijkt}, D_{ijt}, D^{adj}_{ijt}, PR^{adj}_{ijt}, and NR^{adj}_{ijt}; see the definitions in Appendix A of the electronic companion) in the above expected utility function are stochastic and not observable to researchers, but they are observable to physicians. Therefore, we adopt the hierarchical Bayesian approach to derive the full conditional distribution for the posterior means of drug effectiveness and safety as shown in Appendix B of the electronic companion. Also, because researchers do not observe the random coefficients in Equation (3), we need to integrate them out. Given the error structure we impose, our model is a multivariate probit specification, and hence we have the following conditional joint probability of brand choices, detailing, and sampling for physician i for patient k at time t:

$$\begin{aligned} & \Pr(Y_{ikt}, D_{it}, S_{it} \mid \beta_{ij}, \gamma_i, \phi_j, \delta_j, a, b) \\ & = \Pr(Y_{ikt} \mid D_{ijt}, S_{ijt}, \beta_{ij}, \gamma_i) \cdot \Pr(D_{ijt}, S_{ijt} \mid a, b, \phi_j, \delta_j) \\ & = \left[\int_{M_1} \cdots \int_{M_J} (2\pi)^{-(J)/2} |\Sigma|^{1/2} \exp\left(-\tfrac{1}{2}\varepsilon'_{ikt}\Sigma^{-1}\varepsilon_{ikt}\right) d\varepsilon_{ikt}\right] \\ & \quad \cdot \left[\prod_{j=1}^{J} \iint \Pr(D_{ijt} \mid a, \phi_j, \delta_j) \cdot \Pr(S_{ijt} \mid b, \phi_j, \delta_j) \right. \\ & \quad \left. \cdot f(\phi_j, \delta_j) \cdot d\phi_j \, d\delta_j\right], \end{aligned} \tag{7}$$

where $M_l = (0, \infty)$ if $Y_{ijkt} = 1$ and $(-\infty, 0)$ otherwise. $\Pr(D_{ijt} \mid a, \phi_j, \delta_j)$ and $\Pr(S_{ijt} \mid b, \phi_j, \delta_j)$ are probability functions derived from the Equation (2); $f(\phi_j, \delta_j)$ is the multivariate normal probability function given in Equation (4).

4.5. Physician Heterogeneity

We incorporate the patients' characteristics and conditions in the utility function as covariates to capture the observed patient heterogeneity and its impact on physicians' prescription decisions. To measure the effect of unobserved physician heterogeneity on their drug choices, we adopt a hierarchical Bayesian approach (Manchanda et al. 1999, Rossi et al. 1996). Let $\boldsymbol{\theta}_i = (W_i, r_i, \boldsymbol{\beta}_{ij}, \boldsymbol{\gamma}_i)'$, and we have the following heterogeneity equation:

$$\boldsymbol{\theta}_i = \phi \cdot Z_i + \xi_i, \tag{8}$$

where Z_i denotes physicians' demographic characteristics such as specialty (i.e., specialists, PCPs, or Others) and practice location (i.e., office-based, hospital-based, or Others). We further assume that $\xi_i \sim \text{MVN}(0, \Delta)$.

4.6. Likelihood Function

Given the heterogeneity specification above, we have the following unconditional joint probability of brand choices, detailing, and sampling for physician i for patient k at time t:

$$\begin{aligned} & \Pr(Y_{ikt}, D_{it}, S_{it}) = \Pr(Y_{ikt} \mid D_{it}, S_{it}) \cdot \Pr(D_{it}, S_{it}) \\ & = \left[\int_{\theta_i} \int_{M_1} \cdots \int_{M_J} (2\pi)^{-(J)/2} |\Sigma|^{1/2} \right. \\ & \quad \left. \cdot \exp\left(-\tfrac{1}{2}\varepsilon'_{ikt}\Sigma^{-1}\varepsilon_{ikt}\right) d\varepsilon_{ikt} \, d\theta_i\right] \\ & \quad \cdot \left[\prod_{j=1}^{J} \iint \Pr(D_{ijt} \mid a, \phi_j, \delta_j) \cdot \Pr(S_{ijt} \mid b, \phi_j, \delta_j) \right. \\ & \quad \left. \cdot f(\phi_j, \delta_j) \cdot d\phi_j \, d\delta_j\right]. \end{aligned} \tag{9}$$

The log-likelihood is given by

$$\begin{aligned} \ln(L) = {} & \sum_i \sum_k \sum_t \ln(\Pr(Y_{ikt} \mid D_{it}, S_{it})) \\ & + \sum_i \sum_t \ln(\Pr(D_{it}, S_{it})). \end{aligned}$$

4.7. Identification and Estimation Issues

Because of the multivariate probit model setup, for identification purposes, we set the diagonal elements of Σ to one. Therefore, the variance–covariance matrix Σ becomes a correlation matrix; Σ can be identified from the substitution pattern of drugs across doctors and patients over time, and $\boldsymbol{\beta}_{ij}$ are identified from the time-invariant prescription pattern across patients. Similarly, the identification of W_i, r_i, and $\boldsymbol{\gamma}_i$ comes from

the comovements of the prescription behavior of the physician and various drug- or patient-specific information; a, b, ϕ_j, and δ_j are identified from the brand-level detailing and sampling patterns across physicians over time. Ψ is identified from the comovements of the detailing, sampling, and targeting patterns of pharmaceutical firms across physicians over time.

Next, we examine the identification conditions on the parameters in the learning process of drug effectiveness Q_{ij}. Because the physician's prior drug effectiveness beliefs $\bar{Q}_{rj0}$ are identified from initial market shares for observed doctor type r and brand j, we normalize one of the $\bar{Q}_{rj0}$ (i.e., that of the "Others" brand) as zero. Therefore, the prior of other brands are all identified relative to the Others brand. The dispersions on the prior of the drug effectiveness for physicians, namely, $\sigma^2_{rQ_0}$, are identified by the speed of physician's drug adoption at the patient level and how quickly physicians update their drug effectiveness beliefs. A relatively small (large) $\sigma^2_{rQ_0}$ implies that physicians believe the prior is relatively precise (noisy) and therefore rely less (more) on the signals received, which results in slow (fast) learning. The dispersions in the two signals represented by σ^2_{rA1} and σ^2_{rD1} for physicians are identified from the variations of the number of the two signals received by physicians of type r over time, respectively. The true drug effectiveness (Q_{ij}) is identified by the physician's steady-state prescription behavior at the drug level. Note that we have 17 months of data before the first public information release on Avandia in May 2007, which should be reasonably long to reach steady state.[5] In other words, all the parameters in the drug effectiveness learning process are identified before May 2007. This enables us to identify the counterparts in the learning process of drug safety after the first public information release even though both types of learning are present afterward.

We then investigate the identification conditions on the parameters in the learning process of drug safety q_{ij} after the first public information release. For identification purposes, the prior mean of physicians' beliefs on drug safety is set to zero. The dispersions on the prior of the drug safety for physicians, namely, $\sigma^2_{rq_0}$, are identified by the speed of physicians' drug adoption at the patient level after the first public information release and how quickly physicians update their drug safety beliefs. The dispersions in the four signals, represented by σ^2_{rA2}, σ^2_{rD2}, σ^2_{rPR}, and σ^2_{rNR} for physicians, are identified from the variations of the number of the four signals received by physicians of type r after the first public information release, respectively. The true drug safety (q_{ij}) is identified by the physician's long-term prescription behavior at the drug level after the first public information release. The uncertainty on mean bias in the information release and detailing signals for brand j ($\sigma^2_{d_j}$) can be identified because as physicians receive multiple such signals, the variance stemming from uncertainty about drug safety (note that σ^2_{rA2}, σ^2_{rD2}, σ^2_{rPR}, and σ^2_{rNR} are already identified) asymptotes to zero after a large number of these signals are received, whereas the uncertainty stemming from the bias in the signals never gets resolved after receiving multiple signals (for details, see the technical appendix of Mehta et al. 2008).

Given the high-dimensional integrals in the likelihood function in Equation (9), a hierarchical Bayes approach is demonstrated to be a good choice for estimation (Rossi et al. 1996). We use the Gibbs sampler and the Metropolis-Hastings algorithm (if the full conditional distributions are not from any known distribution families) to obtain draws from the full conditional distributions of the parameters (Chib and Greenberg 1995). Additionally, using the data augmentation approach (Tanner and Wong 1987), we treat the unknown utilities U_{ijkt} and the two true drug quality components (Q_{ij} and q_{ij}) as parameters and make draws for them from their own full conditional distributions. Details of the full conditional distributions and the algorithm are given in Appendix B of the electronic companion. We estimate the empirical model using a program coded in C++. The chain for the Gibbs sampler was run for 50,000 iterations. The first 40,000 iterations were discarded as "burn-in" before convergence was attained. The remaining draws were used for inference. Our diagnosis indicates that Markov chain Monte Carlo chains have reached convergence (Gelfand and Smith 1990).

5. Empirical Results

5.1. Benchmark Models

Table 6 summarizes the comparison of our proposed model with various benchmark models using log of

Table 6 Model Comparison

Models	Estimation sample: Log marginal density	Estimation sample: Hit rate (%)	Holdout sample: Hit rate (%)
Model 1—No heterogeneity, learning and endogeneity	−432,090.15	80.94	70.50
Model 2—No learning and endogeneity	−431,565.06	85.04	76.23
Model 3—No learning	−431,562.11	85.05	77.09
Model 4—Learning drug effectiveness only	−431,058.43	87.34	79.11
Model 5—Learning about Actos and Avandia only	−430,491.53	88.46	80.92
Proposed model	−430,481.50	88.74	81.73

[5] This is confirmed by our empirical finding that physicians' perceived drug effectiveness on all drugs reaches steady state in the first two months and remains stable during the data period.

marginal densities and hit rates in both the estimation and holdout sample. Model 1 is a simple multivariate probit model. Model 2 incorporates physician heterogeneity without incorporating physician learning or endogeneity on marketing contacts. Model 3 accounts for marketing contacts endogeneity but does not incorporate physician learning. Model 4 partially incorporates physician learning where physicians only learn about drug effectiveness. Model 5 incorporates physician learning of both effectiveness and safety but only focuses on the learning of Actos and Avandia. Our proposed model clearly has the highest log of marginal density and hit rate in both estimation sample and holdout sample. It also indicates that there is a category-level carryover effect such that physicians learn about other drugs' safety from the information release on Avandia. Because of this strong support, we present the estimation results for the proposed model in the remainder of our discussion. In the tables below, the significant estimates (i.e., zero does not lie in the 95% posterior probability interval of the estimate) are highlighted in bold.

5.2. Estimation Results

Our interest is in understanding the impact of the contradictory information for different types of physicians. Although our model provides parameter estimates for all brands, we focus on the key results and present other estimation results in Appendix C of the electronic companion.

5.2.1. Marketing Contacts, Learning, and Risk Aversion. Consistent with findings from our simple model, the estimates for both detailing and sampling in Table 7 are significantly positive, confirming that increasing marketing activities have a direct and positive persuasive impact on new prescriptions of the promoted drug, including the focal brand Avandia. Because detailing and sampling are in log scale, their positive impact has diminishing marginal return. In addition, the parameter estimate for the interaction between detailing and sampling is negative, indicating that it is important for firms to implement marketing activities carefully and selectively.

Table 7 Estimates for the Utility Function—Nonbrand-Specific Variables

Variable	Estimate	Std. dev.
Log of cumulative patient visits	**0.068**	**0.020**
Log of cumulative detailing	**0.929**	**0.095**
Log of cumulative sampling	**0.955**	**0.217**
*Log of cumulative detailing * Log of cumulative sampling*	**−0.160**	**0.019**
Perceived quality	**1.012**	**0.216**
Risk coefficient	**13.162**	**0.337**

The parameter estimate for perceived quality is significantly positive, confirming that physicians' quality beliefs have a positive impact on their prescribing behavior. The estimate for risk coefficient is positive and significant, signifying that physicians are risk averse in their prescription decisions.

5.2.2. Physician Heterogeneity. We now turn our attention to examining how different types of physicians react to the contradictory information release. The results of the heterogeneity analysis are reported in Table 8. For the log of cumulative detailing, the estimate in the utility function (0.318) and the estimates for specialists (0.211) and office-based PCPs (0.690) in the heterogeneity equation indicate that, overall, detailing has a positive effect on physicians' prescription of the promoted brand, but specialists' prescription decision are less influenced by detailing activities than are the decisions of office-based PCPs ($t = 4.89$, $p < 0.001$).

Similarly, sampling also has positive effect on physicians' prescription choice, although the impact on specialists is much less (−0.021) compared with office-based PCPs (0.417; $t = 2.71$, $p = 0.01$). Office-based PCPs have lower expertise in diabetes treatment, and they are more prone to the influence of sales representatives and sampling efforts. As predicted, hospital-based PCPs are less sensitive to both detailing ($t = 4.08$, $p < 0.001$) and sampling efforts than are office-based PCPs ($t = 7.29$, $p < 0.001$).

Estimates for perceived quality and risk coefficients further confirm that overall diabetes experience, expertise, and self-efficacy may explain differences in reactions. Compared with PCPs, specialists' decisions are relatively more influenced by their beliefs in the quality of the focal brand ($t = 14.76$, $p < 0.001$). In addition, compared with office-based PCPs, specialists are less risk averse ($t = 36.69$, $p < 0.001$) as are hospital-based PCPs ($t = 17.65$, $p < 0.001$).

Table 8 Estimates for the Heterogeneity Function

Variable	Intercept	Specialists	Office-based PCPs	Hospital-based PCPs	Others
Log of cumulative patient visits	−0.279 (0.359)	**0.372** (**0.043**)	0.347 (0.347)	**0.510** (**0.041**)	0.334 (0.356)
Log of cumulative detailing	**0.318** (**0.047**)	0.211 (0.554)	**0.690** (**0.068**)	0.200 (0.588)	0.478 (0.523)
Log of cumulative sampling	**0.475** (**0.051**)	0.021 (0.826)	**0.417** (**0.050**)	−0.860 (0.858)	0.879 (0.677)
*Log of cumulative detailing * Log of cumulative sampling*	−0.204 (0.333)	0.045 (0.450)	0.052 (0.351)	0.555 (0.626)	−0.037 (0.403)
Perceived quality	0.501 (0.804)	**0.083** (**0.015**)	0.627 (0.985)	0.319 (1.215)	−0.424 (0.992)
Risk coefficient	**8.737** (**0.794**)	**−2.310** (**0.885**)	**3.528** (**0.780**)	**−0.823** (**1.199**)	**8.347** (**0.745**)

Table 9 Estimates for the Endogeneity Function of Detailing

Variable	Actos	Avandia	Metformin	Sulphonylureas	Others
Intercept	**0.295** (**0.022**)	**0.257** (**0.032**)	**0.275** (**0.024**)	**0.013** (**0.007**)	**0.890** (**0.048**)
Log detailing coefficient	**−0.036** (**0.018**)	**−0.041** (**0.020**)	**−0.032** (**0.018**)	−0.003 (0.004)	**−0.102** (**0.032**)
Log sampling coefficient	−0.009 (0.016)	−0.028 (0.025)	−0.028 (0.020)	−0.003 (0.004)	**−0.060** (**0.044**)
Log detailing coeff. ∗ Log sampling coeff.	−0.037 (0.035)	−0.043 (0.053)	−0.026 (0.049)	0.001 (0.009)	−0.075 (0.075)

5.2.3. Accounting for Marketing Contact Endogeneity. Table 9 provides parameter estimates on how firms' mean detailing decision is influenced by their understanding of physicians' response to detailing and sampling. Parameter estimates for physicians' response to detailing are negative for Actos, Avandia, and metformin, indicating that firms detail more toward physicians who are less responsive to detailing for these brands. Parameter estimates for physicians' response to sampling are not significant for Actos and Avandia or the generic brands, confirming that firms' detailing decisions are unaffected by their understanding of physicians' sampling response. Further analyses indicates that specialists receive more detailing than do office-based PCPs, and heavy prescribers receive more detailing than light prescribers. This insight was consistent with previous literature (Manchanda et al. 2004).

Table 10 provides parameter estimates on how a firm's mean sampling decision is influenced by its understanding of physicians' response to detailing and sampling. Parameter estimates for physicians' response to sampling are negative for both Actos and Avandia, showing that like detailing, firms sample more toward physicians who are less responsive to sampling for these brands. Parameter estimates for physicians' response to detailing are not significant for all the brands except for Others, indicating firms' sampling decisions are not influenced by their knowledge of physicians' response to detailing for these brands. Also, the estimates for the coefficient of the interaction term between detailing and sampling are negative and significant for Actos and metformin, implying that when providing samples of these two brands to physicians, the firms do target those physicians who are less responsive to both detailing and sampling. Based on the estimated variance–covariance matrix in Equation (4), we also find that the firm's detailing and sampling decisions are correlated as expected.

Table 10 Estimates for the Endogeneity Function of Sampling

Variable	Actos	Avandia	Metformin	Sulphonylureas	Others
Intercept	**1.779** (**0.100**)	**0.419** (**0.032**)	**1.171** (**0.088**)	**0.179** (**0.033**)	**1.573** (**0.077**)
Log detailing coefficient	−0.100 (0.090)	−0.059 (0.034)	−0.094 (0.104)	−0.044 (0.035)	**−0.146** (**0.072**)
Log sampling coefficient	**−0.088** (**0.016**)	**−0.074** (**0.031**)	**−0.207** (**0.098**)	**−0.040** (**0.024**)	−0.117 (0.098)
Log detailing coeff. ∗ Log sampling coeff.	**−0.585** (**0.183**)	−0.030 (0.062)	**−0.304** (**0.132**)	−0.025 (0.052)	−0.026 (0.236)

5.2.4. Physician Learning: Drug Effectiveness and Drug Safety. Estimates of physicians' initial drug effectiveness beliefs are provided in Table 11. All physician types held the highest effectiveness beliefs about Actos at the beginning of the sample period (January 2006). Interestingly, the belief disparity between Actos and Avandia varies across different specialties. Whereas specialists and hospital-based PCPs held much higher effectiveness beliefs about Actos than Avandia ($t = 123.16$, $p < 0.001$; $t = 92.32$, $p < 0.001$, respectively), the office-based PCPs' disparity in effectiveness beliefs is much smaller but still highly significant ($t = 159.11$, $p < 0.001$).

Table 12 provides the estimated variances of physicians' effectiveness beliefs, which presents what information sources influence physicians' learning. Nonsignificant parameter estimates imply that physicians do not learn about drug effectiveness from such information sources. For specialist and hospital-based PCPs, the variance of prior belief is significant whereas variances of patient feedback and detailing

Table 11 Estimated Initial Mean of True General Drug Effectiveness—$\bar{Q}_{rj0}$ in the Learning Model

Variable	Specialists	Office-based PCPs	Hospital-based PCPs	Others
Actos	**0.434** (**0.098**)	**0.428** (**0.062**)	**0.458** (**0.082**)	**0.134** (**0.045**)
Avandia	**−0.402** (**0.131**)	**0.265** (**0.042**)	**−0.137** (**0.039**)	**−0.254** (**0.065**)
Metformin	**0.345** (**0.065**)	**0.283** (**0.060**)	−0.025 (0.070)	0.045 (0.076)
Sulphonylureas	**0.142** (**0.073**)	**0.298** (**0.097**)	**−0.115** (**0.040**)	0.025 (0.059)

Note. The initial effectiveness means for the Others category are normalized to 0 for identification purpose.

Table 12 Estimated Variances in the Learning of Drug Effectiveness

Variable	Specialists	Office-based PCPs	Hospital-based PCPs	Others
Prior variance of the drug effectiveness—$\sigma^2_{rQ_{j0}}$	**1.222** (**0.289**)	**0.211** (**0.001**)	**0.960** (**0.376**)	**0.357** (**0.020**)
Variance of patient feedback signals—σ^2_{rA1}	0.001 (0.001)	**0.048** (**0.001**)	0.003 (0.003)	0.001 (0.001)
Variance of detailing signals—σ^2_{rD1}	0.001 (0.001)	**0.112** (**0.001**)	0.160 (0.328)	1.311 (0.890)

are nonsignificant. Thus both specialists and hospital-based PCPs held strong beliefs about drug effectiveness that were not influenced by patient feedback or sales rep detailing. On the other hand, all parameter estimates for office-based PCPs are significant, indicating that office-based PCPs learn about drug effectiveness from all information sources. Note that the patient feedback variance is the smallest, implying that office-based PCPs learn most about drug effectiveness from patient feedback.

Table 13 provides the estimated variances of all signals for physicians' learning about drug safety. This table is of particular interest because it provides insights on what sources physicians rely on to learn about drug safety. For specialists and hospital-based PCPs, the variances of prior, patient feedback, and negative public information are significant, suggesting that they use patient feedback and negative news to update their beliefs about safety. Furthermore, specialists rely on patient feedback and negative news almost equally, whereas hospital-based PCPs rely more on the negative news. We suspect that this difference is due to the relatively heavier patient workload of hospital-based PCPs. In contrast to the physicians with higher expertise or higher self-efficacy, office-based PCPs rely on all information to update their beliefs about drug safety, including positive news reports and detailing. Overall, office-based physicians appear to be most susceptible to all the biased information sources. Finally, it can be easily observed that negative news reports tend to have a larger across-the-board effect than do positive news reports, confirming the asymmetric effects of negative information.

Table 14 provides estimated perceived bias for different drugs. Only the estimates for Actos and Avandia are significant, revealing that physicians perceive information about only these two drugs' safety to be biased. Because the *NEJM* article was only about the safety of Avandia, this finding is particularly interesting. It appears that the news generated some category-level effect, casting doubt on the safety of its closest competitor Actos, too. However intuitively appealing, the mean of the perceived bias is lower for Actos, suggesting that physicians view information about Actos to be relatively more objective than information about Avandia. The variance of the perceived bias for Avandia is greater than for Actos, connoting that physicians are more uncertain about the extent of bias regarding news about Avandia's safety.

Table 13 Estimated Variances in the Learning of Drug Safety

Variable	Specialists	Office-based PCPs	Hospital-based PCPs	Others
Prior variance of the drug safety—$\sigma^2_{r0_0}$	**0.001** (**0.0002**)	**0.181** (**0.001**)	**0.002** (**0.001**)	**0.280** (**0.018**)
Variance of patient feedback signals—σ^2_{rA2}	**0.001** (**0.0001**)	**0.064** (**0.001**)	**0.004** (**0.001**)	**0.002** (**0.001**)
Variance of positive public info release signals—σ^2_{rPR}	3.946 (4.018)	**0.098** (**0.001**)	1.405 (2.900)	**0.032** (**0.021**)
Variance of negative public info release signals—σ^2_{rNR}	**0.001** (**0.0005**)	**0.045** (**0.001**)	**0.002** (**0.001**)	**0.237** (**0.082**)
Variance of detailing signals—σ^2_{rD2}	5.887 (9.332)	**0.120** (**0.001**)	0.001 (0.001)	**0.568** (**0.223**)

Table 14 Estimated Perceived Bias in the Learning of Drug Safety

Variable	Mean of perceived bias—Δd_j	Variance of perceived bias—$\sigma^2_{d_j}$
Actos	**0.070** (**0.012**)	**0.024** (**0.004**)
Avandia	**0.231** (**0.060**)	**1.288** (**0.390**)
Metformin	0.325 (0.643)	0.047 (0.075)
Sulphonylureas	0.002 (0.004)	1.057 (2.562)
Others	3.053 (5.353)	2.095 (4.288)

6. Managerial Implications

6.1. Predicted Choice Probability and Quality Beliefs Over Time

Based on the estimates of our proposed model and the covariates information, we simulate physicians' prescription choices over time for 10,000 iterations and then compute the average monthly predicted choice probabilities across physicians. The results are shown in Figures 3–8.

Figure 3–5 examine physician heterogeneity in responses over time. With the advent of the disputed information, specialists' prescription probability of Avandia decreases slightly, whereas Actos remains relatively the same with the exception of last two months, where the prescription probability of Actos increases. More interestingly, during the data time period, the prescription probability of Others steadily increases. Recall that the Others category consists of small brands and combination medicines. Hospital-based PCPs are less affected by the contradictory news release—their predicted choice probabilities of all drugs remain relatively stable with the exception of Actos and metformin, which increase in the last two months. On the other hand, for office-based PCPs, prescription probability for Avandia decreases but increases for Actos, metformin, and Others. This indicates that with the contradictory information about Avandia, office-based PCPs seem to move toward "safer" drugs such as metformin, which has been on the market for a long time.

If reactions to the news can be explained by physician experience and self-efficacy, then within PCPs we

Figure 3 Specialists' Predicted Choice Probability Over Time

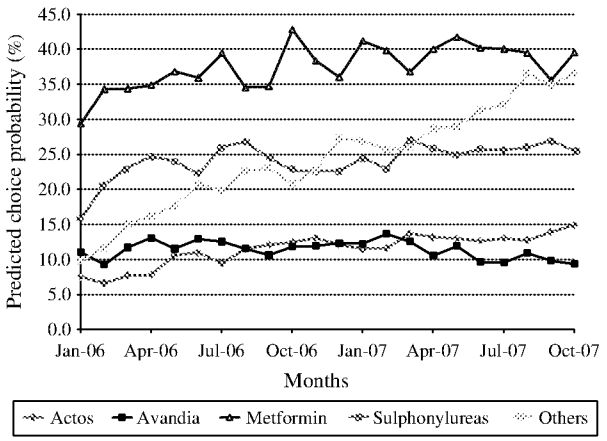


Figure 4 Hospital-Based PCPs' Predicted Choice Probability Over Time

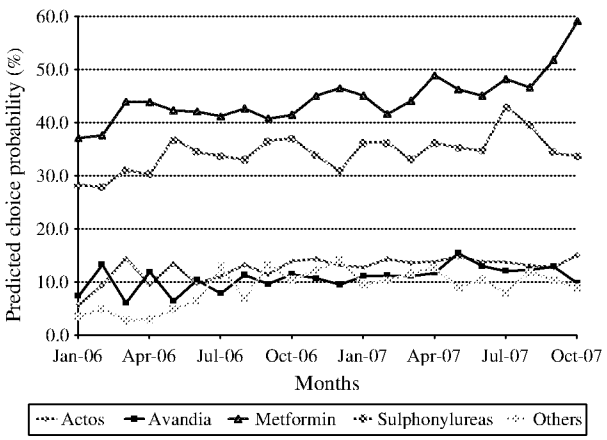
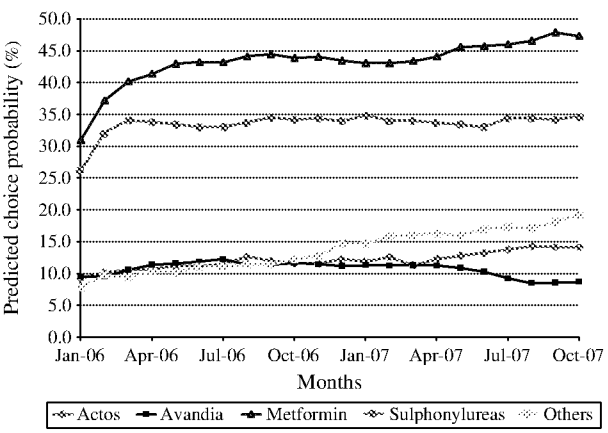


Figure 5 Office-Based PCPs' Predicted Choice Probability Over Time



should also observe differences in behavior between those PCPs who are highly experienced in diabetes (heavy prescribers) and those with more limited experience (light prescribers). We therefore compare PCPs with a total number of patient visits in the top 30% percentile versus the bottom 30% percentile. We compute the normalized choice probabilities by the total choice probabilities across the five brands. Consistent with the experience/self-efficacy account, for heavy prescribers, the normalized Avandia choice probability reduces only by 15.36% from May 2007 to November 2007 but reduces by 30.21% for light prescribers. Additionally, the normalized Actos choice probability for the heavy prescribers increases by 7.02%, but it decreases drastically by 47.61% for the light prescribers. These results provide credence to the explanation that reactions differ because of physician experience and self-efficacy.

Not surprisingly, we find that physicians' beliefs about drug effectiveness are not affected by the news and stay stable during the data period. For brevity, we do not report the results. Physicians' beliefs about drug safety after the first release of the contradictory information are provided in Figures 6–8. Specialists' beliefs about Avandia's safety first actually increase and then remain stable, whereas their beliefs regarding metformin's safety increase. Similarly, hospital-based PCPs' beliefs about both Avandia and metformin safety increase after the news. It appears that both these segments discount the *NEJM* article because of the flawed methodology.

Office-based PCPs' learning on drug safety is very interesting. While their beliefs about Avandia safety decrease, their beliefs about metformin experience a large increase but then decline. Our conjecture is that when office-based PCPs first heard about the news, they became very concerned about Avandia and simultaneously reinforced their beliefs about the well-established metformin as a much safer alternative. With time, their beliefs about metformin safety went back to their pre-news level.

These simulation results show that physicians with varying degrees of experience, expertise, and self-efficacy do respond differently to contradictory news over time. More specifically, specialists and hospital-based PCPs tend to be less likely to be influenced by the news, whereas the less experienced office-based PCPs are more influenced by the new information. These results imply that if the information is contentious, the pharmaceutical firm should gear their marketing efforts more toward PCPs in order to counter the negative impact on, particularly, the less experienced PCPs.

6.2. Revenue Impact of Physician Targeting and Customization of Marketing Mix

To demonstrate how firms can increase revenue by customizing marketing efforts, we simulate the physicians' prescription choices over time and compute the average overall revenue impact (i.e., number of prescriptions) by customizing detailing or sampling or both together for the focal brand. The customization

Figure 6 Specialists' Perceived Mean Drug Safety Over Time

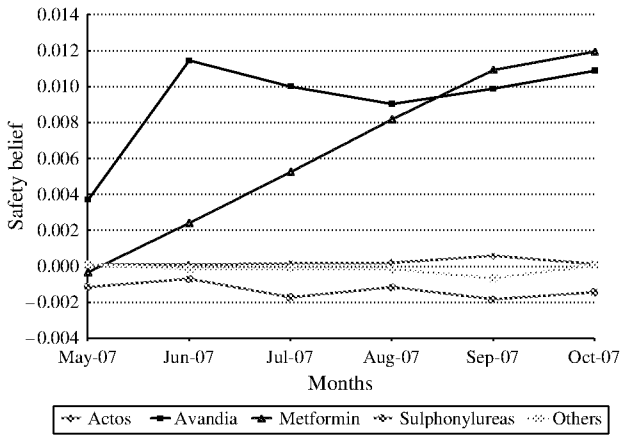


Figure 7 Hospital-Based PCPs' Perceived Mean Drug Safety Over Time

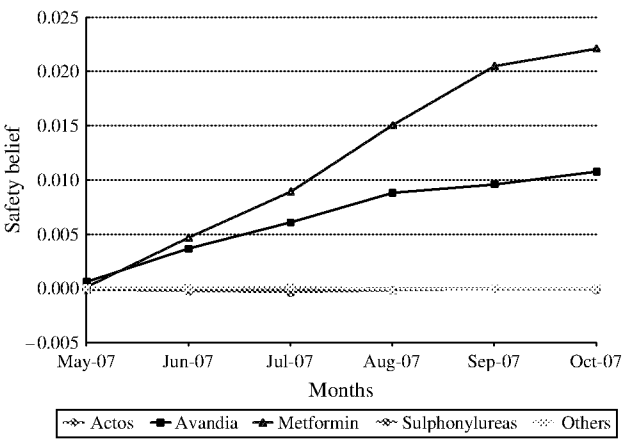
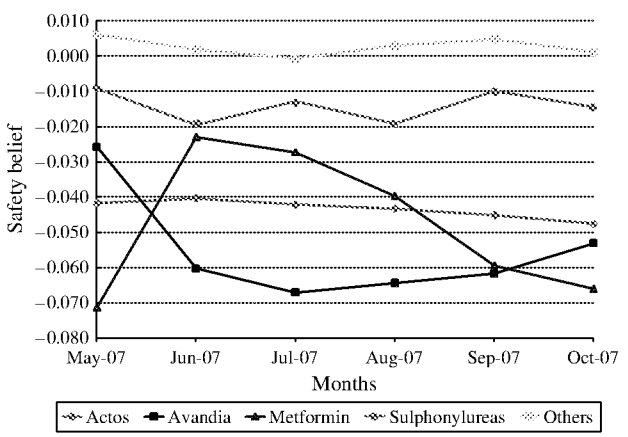


Figure 8 Office-Based PCP's Perceived Mean Drug Safety Over Time



rule is as follows: we double it if the sign of the estimated individual-level coefficient of the covariate (detailing or sampling) for the focal brand is positive and reduce it to zero if the sign is negative. The results are presented in Table 15. Please note that unlike other research (e.g., Erdem and Keane 1996, Sun and Li 2011), we do not optimize in our policy experiments.

Table 15 Revenue Impact of Targeting on Avandia Prescriptions

Customization of marketing efforts	% change of total prescriptions	% change of total prescriptions after news broke on Avandia in May 2007
Customizing detailing only	29.10	121.53
Customizing sampling only	29.92	122.94
Customizing both detailing and sampling	46.99	148.74

From Table 15, we can clearly see that customizing sampling effort has slightly higher revenue impact (a 29.92% increase over the actual number of Avandia prescriptions in the data) compared with customizing detailing effort (a 29.10% increase). If we focus on the time after the first information release, the change in revenue percentage by customizing detailing or sampling is even more dramatic, with 121.53% and 122.94% increases, respectively. Finally, the customization of both detailing and sampling efforts results in an even higher revenue increase with 46.99% or 148.74% increases overall and post news, respectively.

7. Conclusion and Future Research

In this paper, we examine how decision makers respond to contradictory information about products where the implications on whether to persist with or abandon the product are not readily apparent. Our primary focus is on how product quality beliefs are updated on the information release and on the differences in the responses across the decision makers. We speculate that experience, expertise, and self-efficacy play a role in how such information is integrated with current quality beliefs. We investigate physician reactions to the release of contradictory information on Avandia, one of the leading drugs for treatment of type II diabetes. In particular, we are interested in how beliefs about drug effectiveness as well as drug safety are updated. The process was modeled within a Bayesian learning framework, allowing for physicians to update their beliefs from multiple signals: positive and negative news releases, the firm's marketing effort (detailing), and patient feedback. Unlike prior Bayesian learning models, we consider that some information sources may be biased in that they provide an opinionated point of view. We categorize news reports as either positively or negatively inclined on whether physicians should persist in prescribing Avandia. Furthermore, detailing is viewed to be positively biased.

The results show that physicians with relatively higher expertise and self-efficacy (specialists, hospital-based PCPs, and heavy prescribers) are less likely to

be affected by the contradictory information release. Specialists and hospital-based PCPs are similar in that they rely on their prior beliefs to gauge drug effectiveness, but the office-based PCPs are also influenced by patient feedback and detailing. Specialists and hospital-based PCPs are also similar in how they update beliefs about drug safety: both rely on patient feedback and negative news, but office-based PCPs are open to be influenced by all sources including detailing. We also find evidence that the safety issue about Avandia resulted in spillover concern to close competitor Actos.

The news results in different patterns of brand switching. Office-based PCPs shift to older, well-established drugs like metformin. Interestingly, hospital-based PCPs also shift to metformin, but specialists switch to other drugs. Higher risk aversion on the part of hospital-based PCPs accounts for the difference in behavior.

Based on the estimates of the proposed model, we conduct several counterfactual policy experiments using simulation. In the event of contradictory expert recommendations about the product, we find that the targeting effort of the focal brand should be geared more toward PCPs with low expertise or self-efficacy than specialists. We also determine that customizing the marketing efforts of the focal brand can increase its revenue by 46.99% overall and by 148.74% after the initial news release.

Our proposed model also has several limitations that temper the results but provide future research avenues. First, we have only five months' data after the first Avandia warning. If more and better data are available, it will be interesting to examine different physicians' long-term prescription behavior and the dynamics of the physicians' preference changes before and after the contradictory information release. Second, our sample of non-office-based PCPs is relatively small. Here, a latent-class model can be a valuable alternative to incorporate physicians' heterogeneous learning. Third, we do not consider patient learning and the possibility of knowledgeable patients impacting physician decisions. Understanding how exactly patient input is factored into this decision and the potential for patient learning to influence physicians is worth further exploration. Fourth, we do not observe drug prices and how much the patient actually paid in the data. That information will help to explain behavior of pre-diabetes patients. Unlike Erdem and Keane (1996) or Dong et al. (2009), this model does not include physicians' potential forward-looking behavior or a firm's strategic behavior. Finally, because of data limitations, our analysis is restricted to one drug category. The availability of other data categories will further enrich our insights and allow generalizability.

8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

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