EELCO KAPPE

The Effectiveness of Pharmaceutical Marketing

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De effectiviteit van farmaceutische marketing

THESIS

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born in 's-Gravenhage

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Eelco Kappe
Rotterdam, May 2011

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Introduction

Healthcare costs constitute a substantial part of GDP around the world. In 2009, health expenditures in the U.S. accounted for 17.6% of GDP (more than $8,000 per person). This is the second highest in the world and the share is expected to rise in the coming years. Prescription drugs account for more than 10% of the healthcare expenditures. Global pharmaceutical sales of prescription drugs reach $880 billion in 2011, of which 38% is realized in the U.S. market (IMS Health). The pharmaceutical industry is an important contributor to the health and prolonged lives of people, but at the same time it is largely a for-profit industry.

The pharmaceutical industry is a prime example of a life science industry (Stremersch and Van Dyck 2009). It has two main characteristics differentiating it from other industries: (i) it is highly regulated as it deals with people's health and (ii) it is a science-based industry.

Regulated Industry

The pharmaceutical industry worldwide is one of the most regulated industries. In the U.S., the Food and Drug Administration (FDA) passed in 1906 the Pure Food and Drug Act. This allowed them to control the labels of drugs and is an important tool to safeguard the public health. It also regulates the marketing of prescription drugs in the interest of society and states that firms should provide balanced information about the risks and benefits of the drug.

The strongly regulated nature of the pharmaceutical industry has two important implications for marketing research. First, research in the pharmaceutical industry requires industry-specific knowledge. While marketing research often asks for knowledge that is generalizable across industries, this might limit the understanding of specific industries (Stremersch and Van Dyck 2009). Regulations are in place for, amongst others, the approval process of new drugs, the scientific testing of these drugs, the patent protection system and the form and content of promotion efforts. These regulations are often different across countries and updated over time. In order to do rigorous research in the pharmaceutical industry these regulations need to be taken into account, which might subsequently limit the generalizability of the outcomes to different industries or markets.

Second, the context-specific regulations also provide advantages for marketing research. Strict regulations might limit the number of variables that play a role for a particular problem. For example, the restriction of direct-to-consumer advertising (DTCA) in many countries allows the researcher to more easily isolate the effect of personal selling on prescriptions. The regulations also contribute to the structure and amount of data

collection in the industry. As regulations standardize industry practices, the industry often delivers high quality and consistent data. For example, the patent system allows the researcher to classify new products according to the type of innovation and subsequently to investigate the sources and consequences of different types of innovations (Sorescu et al. 2003). In addition, to check the compliance with the regulations, structured and rich data is required. IMS Health, a main data provider for the industry, for example, collects data on the content of thousands of sales calls per year. The richness and structure of the data in the pharmaceutical industry provides many unique opportunities to study marketing phenomena in-depth, which can lead to generalizable insights in substantial marketing phenomena, such as innovations and product bundles.

Science-Based Industry

Science-based industries comprise a substantial part of the economy and are very important for economic growth (Narin et al. 1997). Examples of industries heavily dependent on science are biotechnology, chemicals, medical electronics, nanotechnology, pharmaceuticals and semiconductors (see Grupp 1996; Narin 2000). Products sold in science-based industries are markedly different from those in other industries. Products in science-based industries have a higher number of science papers cited in their patents (science linkage) as compared to products in other industries (Pavitt 1984; Narin 2000). In addition, scientific reviews appear prior to and during the lifecycle of a product providing information on the product. As the pharmaceutical industry is a prototypical example of a science-based industry, this has three consequences for pharmaceutical marketing research.

First, it is important to investigate the role of scientific reviews in this industry (e.g. Azoulay 2002). Products are only approved to the market if they are sufficiently supported by scientific reviews, which subsequently also influence their success on the market. In addition, firms build on the scientific reviews in their marketing efforts as they provide important product information. Hence, it is important to take the role of science in this industry into account.

Second, science-based industries are characterized by substantial investments in R&D. Pharmaceutical firms spend around 20% of their revenues on R&D (Shankar 2008). The rewards to R&D, in the form of an approved drug, can be very large as the drug is protected by a patent providing the firm with substantial market power (Scherer 2004). For example, Lipitor, the best selling drug in the world, generated almost $13 billion in sales in 2007, while the production costs of the drug are small. However, the development costs of prescription drugs are also very high. DiMasi et al. (2003) estimate the average costs of developing an approved drug in 2000 to be $802 million and $1.3 billion for a biologic

(DiMasi and Grabowski 2007). Pfizer, for example, spent between 2000 and 2008 a staggering $60 billion on R&D, while only 9 new drugs were approved during that period. The industry suffers from a decline in new drug approvals, even though the R&D investments are higher than ever (Munos 2009). This requires pharmaceutical firms to focus on new forms of innovations.

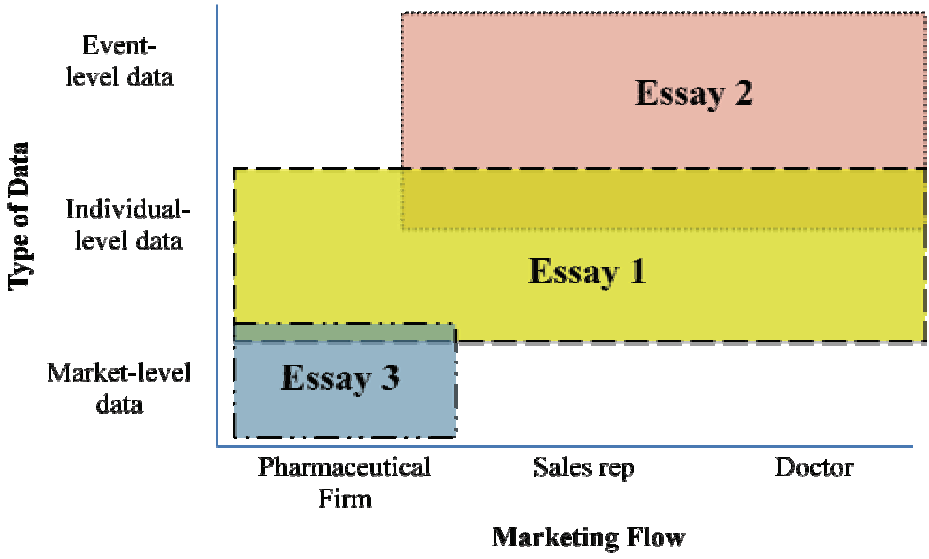
Third, the reliance of pharmaceutical products on science may influence demand. Demand is influenced as not the end consumer (the patient) decides on whether to buy a product, but an expert (the doctor). This also affects the pharmaceutical marketing allocation of firms. Pharmaceutical firms heavily spend on marketing (around 10% of their revenues, Shankar 2008) and personal selling – also referred to as detailing – is the main promotional instrument in the pharmaceutical market. It involves a sales person that details the (science-based) drugs of his company to the doctor.

Overview of the Dissertation

In this dissertation, I study relevant pharmaceutical marketing problems using empirical models. Figure 0.1 gives an overview of the essays of this dissertation and classifies them along the flow of pharmaceutical marketing on the horizontal axis and the type of data on the vertical axis. The flow of pharmaceutical marketing goes from the pharmaceutical firm (the initiator), by means of the sales rep (the intermediary) to the doctor (the decision maker).

In the short discussion below on the three essays of this dissertation, I will give an overview of the type of data used to analyze various market players and the accompanying model used. In addition, I relate the essays to the two main characteristics of the pharmaceutical industry discussed above.

Figure 0.1: Overview of the Dissertation



Essay 1: Gauging a Policy Shift

Pharmaceutical firms invest heavily in their sales force, also referred to as detailing, and expenditures have more than doubled over the last decade to $25 billion in 2005 (Donohue et al. 2007). There is an extensive debate in the academic literature in marketing about its effectiveness (see Essay 2). Public policy administrators and health care providers are concerned with the social welfare implications of intensive detailing to doctors. The public opinion, at large, is that pharmaceutical firms spend too much on marketing their products to doctors (USA Today 2008). Even multiple pharmaceutical firms such as AstraZeneca, BMS, GSK and Wyeth speculate that sales forces have grown too big and some publicly announced that they are considering dramatically cutting the size of their sales force (e.g. BusinessWeek 2007). One important reason why firms have not cut their detailing is that it is very challenging to predict the outcomes of a drastic change. In the first essay, I develop a framework – called data enrichment – to gauge the implications of a firm-initiated yet-to-be-enacted policy shift and apply that to various downward policy shifts in detailing. It requires the integration of revealed preference data on prescriptions and detailing at the doctor level, enriched with stated preference data on the detailing allocation of firms under different policy shift scenarios. The data enrichment framework not only provides valuable insight into the outcomes of a downward policy shift in detailing to end the detailing arms race, but also provides a framework for future analyses of a wide range of policy shifts.

Essay 2: Pharmaceutical Sales Message Content

The marketing literature has found a large heterogeneity in pharmaceutical sales call effectiveness (e.g. see Fischer and Albers 2010; Kremer et al. 2008; Mizik and Jacobson 2004; Narayanan et al. 2005; Venkataraman and Stremersch 2007). While various explanations have been given for this heterogeneity no one has investigated the role of the information content provided in the sales message, while Churchill et al. (2000) consider the sales message to be the core of personal selling. In the second essay, I examine (1) how responsive doctors are to information provided across different product attributes; (2) whether firms present a positively biased information set to doctors; (3) whether doctors are more or less responsive to positively biased information in sales calls. This requires a model that estimates the effectiveness at the sales call level, while controlling for the possible endogeneity of sales call allocation and possibly the content of the sales call. To estimate the effectiveness at such a detailed level while controlling for endogeneity a hierarchical Bayesian vector autoregressive (VAR) model is used. Positively biased information is operationalized by linking the information content to scientific information on the drugs. This gives detailed insights in how firms can adjust their messaging to optimize doctors' detailing responsiveness. In addition, it fits in a stream of research relating the advertising content to advertising responsiveness, conducted for television advertising (e.g. Anderson and Renault 2006; Chandy et al. 2001; Lodish et al. 1995) and for print and banner advertising (e.g. Bertrand et al. 2010; Hanssens and Weitz 1980; Lohtia et al. 2003; Wedel and Pieters 2000).

Essay 3: Science-Based Markets

The pharmaceutical market is a prototypical example of a science-based market. Products in science-based markets are largely supported by scientific reviews that appear prior to and during its lifecycle. As the outcomes of scientific reviews differ, in Essay 3, I investigate 1) how do scientific reviews affect marketing expenditures to users and experts and 2) to what extent do scientific reviews affect sales. It employs a comprehensive dataset on scientific reviews for an important category in the pharmaceutical industry and combine that with brand-level sales and marketing. A vector error correction (VEC) model is used to model the sales and marketing expenditures across brands as a function of scientific reviews. Limited data availability induces to pool the parameters across brands, while controlling for brand-specific factors. The essay gives not only important insights in how firms can use science as a marketing tool or to adjust their marketing mix, but also shows that omitting scientific evidence from the analysis biases marketing responsiveness

coefficients. In addition, it relates the role of scientific reviews to user and expert reviews to build a bridge with this popular stream of literature.

Bucking the Trend in Pharmaceutical Detailing: Enriching Data to Gauge a Policy Shift

Essay 1*

*This essay is based on a paper in collaboration with Stefan Stremersch and Sriram Venkataraman.

Bucking the Trend in Pharmaceutical Detailing: Enriching Data to Gauge a Policy Shift

Abstract

In this study we evaluate the arms race in pharmaceutical detailing and gauge the consequences of various policy shifts that may be able to buck the trend. We provide an alternative decision support tool for firms and public policy makers that aids in gauging the implications of a policy shift ex ante. We combine *revealed* prescription and detailing data with *stated* detailing data obtained from managers through a conjoint experiment. Our approach offers an alternative to policy shift analyses involving either an all reduced-form approach or a fully structural approach. It also provides a more detailed and quantitative assessment of a policy shift than the general scenario planning approach.

Our results show that small detailing changes are not able to buck the trend, but a drastic reduction in detailing by the market leader is needed to generate a profitable market outcome for all players. The initiator of the shift is always better off and the followers show mixed outcomes on profitability. Furthermore, initiating a downward policy shift always reduces the size of the market. Given the controversy surrounding this arms race, the results imply that market leaders should take responsibility, otherwise the government should consider intervention in the market.

"We don't need those large sales forces to do the job. We need them because the competition is doing it… We do believe there is an arms race out there in terms of sales forces and that if you were to redesign the system from scratch you would end up with smaller sales forces." -- Jean-Pierre Garnier, CEO, GlaxoSmithKline (2005).

Introduction

Pharmaceutical firms invest heavily in their sales force, which is strategically allocated among physicians (Manchanda et al. 2004). Pharmaceutical sales force investments, also referred to as detailing, have more than doubled over the last decade to $25 billion in 2005 (Donohue et al. 2007). There is an extensive debate in the academic literature in marketing over whether such intensive detailing positively affects prescriptions, with some authors finding positive, but often modest, effects (e.g. Manchanda and Honka 2005; Mizik and Jacobson 2004), while others find that the effects can also be zero or negative (Kremer et al. 2008; Leeflang and Wieringa 2008; Venkataraman and Stremersch 2007). At the same time, public policy administrators and health care providers are concerned with the social welfare implications of intensive detailing to physicians. The public opinion, at large, is that pharmaceutical firms spend too much on marketing their products to physicians (USA Today 2008).

Multiple firms such as AstraZeneca, BMS, GSK and Wyeth speculate that sales forces have grown too big and some publicly announced that they are considering dramatically cutting the size of their sales force (BusinessWeek 2007; Philadelphia Inquirer 2005; Wall Street Journal 2003). These announcements are a form of signaling, typically done to elicit competitive reactions (Heil and Robertson 1991). But bucking the industry trend can be a risky business as is also illustrated in the Wall Street Journal (2003): "Like cold war enemies, no drug company is willing to be the first to disarm its troops". Firms need sound decision-support tools to gauge the consequences of a substantial policy shift before the policy shift is implemented (Ailawadi et al. 2005). A policy shift is a considerable change in an agent's belief about how to attain its core goals reflected in the implementation of a sustained change in the agent's actions. The policy shift can be triggered either by a firm or another player in the environment. The government might take its responsibility regarding the pharmaceutical detailing arms race as most stakeholders indicate it has escalated. While this can be done by regulations, 'soft coordination' is most commonly pursued, whereby the government talks with the different agents to coordinate a change. For these situations studies that help to gauge the consequences of a policy shift are very helpful.

Our objective in this paper is to gauge the consequences of a downward policy shift in pharmaceutical detailing. We provide an alternative decision support tool for firms

and public policy makers that aids in gauging the implications of a policy shift. This study also provides some validation exercises for our results.

Our method entails the enrichment of revealed data on which we estimate a demand-supply system, with stated data. The stated data are inventoried through a managerial conjoint experiment under various conditions before and after a policy shift. Enriching the data gets around some of the assumptions inherent to the study of policy shifts with reduced-form and structural models using panel data only. Firms and academics have mainly focused on general scenario planning (Schoemaker 1995) to analyze policy shifts. Since research on gauging more specific policy shifts is lacking, firms often take no radical action during an arms race or resort to costly and time-consuming field experiments, which often lack generalizability to markets outside the test market. Our approach is particularly attractive to aid in decision making on a policy shift ex ante, without having to make any assumptions on inter-firm conduct.[1]

The results show that when the market leader decreases detailing by 40%, all competitors follow its lead, leading to substantially higher profits for all firms in the market. Second, for every large-scale policy shift we consider, the initiator increases his profit margin in the long run. Third, we find that every downward policy shift reduces the category size. The results have important implications for managers and public policy. They show that market leaders should take their responsibility in the pharmaceutical arms race by cutting their detailing substantially. If the market players fail to take action, the government should respond by either coordinating marketing expenditure decreases together with the pharmaceutical firms or enacting lawa to restrict detailing.

As our goal is to gauge a policy shift before it is initiated, we do not actually observe the outcome of the policy shift. Therefore we resort to several alternate approaches to validate our results. First, the empirical literature confirms the role of the market leader to set new competitive market conduct. Second, we compare our outcomes with other industries and another detailing shock in the pharmaceutical industry. Furthermore, the answers we received from the experts to whom we submitted our results shed further light on our findings.

Our approach can also be used in other settings, such as gauging the consequences of the Dutch retailing price war Albert Heijn initiated (Van Heerde et al. 2008), the decision of a major oil company to invest heavily in alternative energy sources or a regulatory change in the U.S. capping total detailing expenditures. Such large policy shifts

[1] In our model, we do not have to specify the conduct between firms, i.e. physician-specific Bertrand-Nash competition/collusion/share maximizing/sales maximizing model. Our approach is therefore agnostic to the nature of inter-firm conduct.

all have one thing in common, i.e. they shake up the market and historical patterns do not continue to hold anymore. In these cases, one should carefully consider which information from the past can be used to predict the future, and for which facets, additional information should be collected to come to sensible predictions on the consequences of a large policy shift.

We proceed by presenting the conceptual background of our study, followed by a description of our revealed prescription and detailing data, our stated detailing data and the data enrichment procedure. We then discuss the model, results and validation and conclude with the conclusion and implications.

Background

Firms typically analyze future policy shifts using the general scenario planning approach, while the marketing literature has resorted to more quantitative models, both reduced form and structural. All have their own merits and demerits which we discuss in turn. We employ a data enrichment approach which combines the strengths of scenario planning and quantitative models and overcomes some of their limitations to gauge a policy shift. Next, we discuss three methods employed in the literature to gauge a policy shift and contrast them with the use of data enrichment.

A first alternate method is to forecast the consequences of a policy shift from actual variation in pre-shift data, without any other input. However, data on actual and past behavior typically do not contain a policy shift, similar to the one under consideration, and hence one has to extrapolate beyond the policies observed in the data. This method suffers from the Lucas critique, which states that response parameters can change as a function of policy changes (Lucas 1976). Gauging future policy shifts may lead to inaccurate predictions, as response parameters may change (Chintagunta et al. 2006; Van Heerde et al. 2005). Reduced-from models can, however, be used to analyze past, rather than future, policy shifts. Excellent examples are Ailawadi et al. (2001), Chen et al. (2009) and Van Heerde et al. (2008).

A second alternate method is to specify a structural model that explicitly models the market structure and the supply-side conduct of firms based on economic premises (for an overview, see Bronnenberg et al. 2005; Reiss and Wolak 2003). Such method overcomes the Lucas critique and can be used to forecast the consequences of a policy shift and/or a change in the market structure (Nevo 2000). Successful examples of full-information-based structural models are Ailawadi et al. (2005), Chintagunta et al. (2003), Chu et al. (2007) and Nevo (2000). However, the usefulness of this method hinges on two

assumptions. First, it is dependent on the correct supply-side firm conduct specification, which otherwise results in inconsistent demand-side parameters.[2] Second, these models assume already that firms act optimally according to the specified objective function, which is often in contradiction to the reason firms want to initiate policy shifts (Bronnenberg et al. 2005; Chintagunta et al. 2006).

A third alternate method is scenario planning (Schoemaker 1993; 1995). Scenario planning includes 'focused descriptions of fundamentally different futures presented in coherent script-like or narrative fashion'. This method is popular among major firms to anticipate changes in their environment, such as the credit crisis, globalization, innovations and deregulations (Hodgkinson and Healey 2008). It is found to be successful in structuring the minds of managers, in identifying strengths and weaknesses within a company and in improving firm performance (Phelps et al. 2001). However, the method lacks the details needed to implement specific strategies and more detailed quantitative extensions are needed to gauge the consequences of a policy shift. Cooper (2000) provides a successful extension of scenario planning, by means of a Bayesian network, to plan the marketing of radically new products.

In contrast, our data enrichment approach offers a limited information alternative to evaluating policy shifts that borrows elements from the structural and scenario planning approaches discussed above. Like the structural approach, we estimate a structural demand model using revealed choice data. Akin to the scenario planning approach we present managers with various supply-side scenarios. However, unlike the traditional scenario approach our scenarios are presented to managers via a conjoint survey which allows us to quantitatively elicit their responses to different scenarios.

Data enrichment[3] usually refers to the statistical fusion of two or more datasets and has been successfully used by others. Among many other applications, it has been used to enrich panel data (Mark and Swait 2004; Swait and Andrews 2003), to improve the accuracy of the estimation (e.g. Albuquerque and Bronnenberg 2009; Imbens and Lancaster 1994) and to model markets with indirect network externalities (Gupta et al. 1999).

Our data enrichment approach allows us to complement revealed market data (both on the demand- and supply-side) with stated supply-side reactions to hypothetical market scenarios. Such an enrichment of revealed with stated data provides unique and valuable insights (see Louviere et al. 2000 for a full discussion and Whitehead et al. 2008 for a multidisciplinary overview). Our modeling philosophy is easily portable to other

[2] Provided the demand and supply-side models are jointly estimated.
[3] Data enrichment is sometimes also referred to as data fusion.

industry settings than the one here. It enables one to gauge policy shifts that cannot be generalized beyond the policy variation observed in the revealed data. Our approach requires the firm to gather new stated data, however, without having to incur the costs of running large-scale field experiments or rely on insights from possibly inconsistent structural analysis parameters.

Compared to the methods discussed above our data enrichment approach provides three key advantages to gauge the outcomes of a policy shift ex ante. First, it allows us to account for competitive reactions without making any (optimality) assumptions on the nature of firm conduct. Second, it explicitly deals with the Lucas critique. Third, our approach allows us to combine the strengths of both types of data: the high validity (based on actual decisions) of revealed data and the good statistical properties (larger variation) of stated data.

Data

We obtain stated detailing data, from a conjoint experiment, to enrich revealed data on prescriptions and detailing obtained from a large physician panel. We discuss both datasets below, each in turn. We also explain how we transformed the conjoint data to allow the integration of both datasets.

Revealed Prescription and Detailing Data

We observe, in the statin category, the discrete number of monthly self-reported prescriptions and details for a U.S. panel of 1,585 general practitioners for the period August 2003 through May 2004. The panel, collected by a market research firm, is representative for the U.S. physician population, both in terms of practice size and geographically. In our analysis, we focus on the four major drugs in the market during this period, namely Lipitor (Pfizer), Zocor (Merck), Pravachol (BMS) and Crestor (AstraZeneca), which was introduced to the market in August 2003.

Stated Detailing Data

We have obtained stated detailing data from an online conjoint experiment, in which we presented practitioners with hypothetical policy shifts. Typical profiles of respondents are marketing or sales operations directors of major companies like GSK, Johnson & Johnson and Abbott.[4]

[4] Note that our approach does not warrant the respondents of the stated-choice task to be managers in competing firms, i.e. needs competitor participation. The respondents can be consultants who have had experience in managing physician-directed detailing themselves or for their clients. The assumption is that our respondents

We presented them with the actual market situation of the four major drugs in the market, including information regarding the manufacturer, patent protection time and market share. To circumvent confidentiality and social desirability issues, our respondents did not inform us on their own company policy. They were asked to infer the detailing allocation behavior toward different physician types for two of the four major players in the statin category.[5] We obtained a list of potential key informants from Quintiles Transnational Corporation, which is the largest provider of sales force services in the pharmaceutical industry. We contacted potential informants by phone or email to screen them on their involvement in pharmaceutical sales force allocation and size decisions. Ultimately, 26 respondents out of the 63 respondents who passed our initial screening participated, achieving a response rate of 41%. On average they have more than ten years of experience in the pharmaceutical industry.

To consistently inform them, the respondents were first given some background information on the market situation and some pros and cons of hiring and firing sales reps. Following the guidelines of Ben Akiva et al. (1994), we provided respondents with a *base scenario*, in which they were asked to take the position of one firm in the statins category and allocate detailing across four physician types. The base scenario mimics the situation in the panel data and intends to measure the validity of the stated data. A physician type is described by three attributes, having three levels each, yielding 27 types. Given the limited number of types, we created a full-factorial design and used an interchange heuristic to minimize the correlation between attributes within a respondent's profiles. The first attribute is the physician's prescription volume, with levels: low (two prescriptions per quarter), middle (four prescriptions per quarter) and high (six prescriptions per quarter). The second attribute is the physician's responsiveness to detailing, whether low, middle or high. The third attribute is competitive detailing, with levels low, middle and high, respectively corresponding to one, three and five details per quarter. The specific levels for prescription volume and detailing are informed by the revealed prescription and detailing data. We chose three-level attributes to allow for nonlinear effects and not succumb to the number-of-levels problem (Wittink et al. 1989).

Next, we presented the respondents with three *hypothetical policy shifts* and asked them to indicate the expected percentage change in the total size of the firm's sales force and, again, to allocate their detailing across four physician types. These three hypothetical policy shifts were randomly drawn from a total set of six such shifts, namely: (1) 10%

know the nature of the supply-side conduct between firms and respond accordingly, but the econometrician has some uncertainty about the nature of inter-firm conduct.

[5] As a reviewer pointed out, this does not enable the respondent to extract private company information.

detailing reduction for Lipitor; (2) 25% detailing reduction for Lipitor; (3) 40% detailing reduction for Lipitor; (4) 10% detailing reduction for Pravachol; (5) 25% detailing reduction for Pravachol; and (6) 40% detailing reduction for Pravachol.

Respondents, in total, go through three cycles of one base scenario and three hypothetical policy shifts. In order to reduce cognitive effort, the four physician types among which they need to allocate detailing remain constant within a cycle, but vary across cycles. See Appendix 1A for more details on the conjoint experiment.

Enrichment Procedure

To enrich the revealed data with stated data and allow for its joint estimation, we first need to transform both to the same scale. The dependent variable for both datasets is transformed into the average monthly number of detailing visits per physician. The explanatory variables for both datasets are dummies indicating whether the physician scores low, middle or high on the three attributes, prescription volume, responsiveness to detailing and competitive details received.

To transform the revealed data, we calculated as our dependent variable the average number of detailing visits for each physician in the last three months of our panel data. Then we classified, based on the outcomes of our demand-supply model discussed below, each of the physicians as one of 27 types, based on their score (low, middle, or high) on each of the three attributes: prescription volume, responsiveness to detailing and competitive details.

The stated detailing data is obtained from "allocation of points" questions (the conjoint tasks), where the respondents had to allocate 100 detailing visits over four different types of physicians. Per conjoint task, we multiplied the stated allocation with the total number of detailing visits these four physician types jointly received, on average, in the last three months of the panel data.[6] For every respondent, the dependent variable is now the average monthly number of detailing visits under the *base scenario*. For the hypothetical policy shifts, we adjust these numbers by the specified increase/decrease in the size of the sales force.

Next, we test whether the revealed and stated detailing data can be pooled under the base scenario by stacking both datasets and estimate the following equation:

$$\begin{bmatrix} Det_{revealed} \\ Det_{stated} \end{bmatrix} = \alpha + \begin{bmatrix} X_{revealed} \\ \mu X_{stated} \end{bmatrix}' \begin{bmatrix} \beta_{revealed} \\ \beta_{stated} \end{bmatrix} + \begin{bmatrix} \varepsilon_{revealed} \\ \varepsilon_{stated} \end{bmatrix}, \qquad (1.1)$$

[6] Under the *base scenario*, both datasets have now the same number of average detailing visits.

where *Det* and *X* are detailing and the explanatory variables respectively and the subscripts *revealed* and *stated* refer to the data source. α is a common constant for both datasets, μ is the scale factor and the vector β contains source-specific coefficients.

The two datasets have different sources of variation. First, the uncertainty about the attributes and decision environment may differ in both datasets. Second, the stated data reflect respondent heterogeneity while the revealed data contain implemented policies. Third, the stated data assume perfect targetability of respondents. To treat these data-source-specific differences we allow for a scale factor and heteroscedastic errors in Equation (1.1) and conduct a two-step test for poolability. In the first step, we allow for an unrestricted scale factor μ for the stated data and conduct a Chow test on $\beta_{revealed}=\beta_{stated}$. Conditional on acceptance of the Chow test, we can test whether μ is equal to one using a likelihood ratio test.[7]

If both tests are passed, the datasets can be pooled directly. In case the models only differ by a scale factor μ, we can still pool the estimations and make forecasts based on our conjoint data, taking the scale factor into account. If the parameter equality test fails, we should impose fewer restrictions on the parameter equality and compute additional scale factors between parameters (see e.g. Mark and Swait 2004; Swait and Louviere 1993). The scale factor can be interpreted in the same way as the external effects adjustments in conjoint analysis (see Orme and Johnson 2006). Recognizing the various differences between the stated behavior of respondents and real-world behavior, they propose simple adjustments, such as a scale factor, to improve real-world predictions.

An assumption underlying our policy shift simulations is that the demand side is stable over time, irrespective of the policy shift concerning detailing (i.e. not subject to the Lucas critique). We assume physicians to act in the patient's best interest and to not change their decision process after a marketing policy shift.[8] If one wishes to test or relieve this assumption within our framework, one could do so by collecting additional data about the behavior on the demand side after the policy shift.

Model

Our data enrichment approach combines a demand-supply model estimated on revealed data, which does not contain the anticipated policy shift, with a supply model on stated responses in a conjoint experiment to the policy shift. We first discuss the demand-

[7] Note, that our data enrichment approach does not require us to make any assumptions on inter-firm conduct.
[8] Structural models also make the same assumption while conducting counterfactual experiments. Because the model parameters in this approach are behavioral primitives, the Lucas critique may be allayed and probably not even hold. Since our demand-model is a structural model the same pros and cons of the structural approach pertaining to demand-side parameters hold in our model as well.

supply model calibrated on secondary data and its estimation. Then we turn to the stated supply model estimated on the conjoint data. We end by discussing the operationalization of the enrichment procedure.

Demand-Supply Model on Revealed Prescription and Detailing Data

Our demand-supply models physician's prescription behavior and accommodates non-randomness in detailing allocation, to account for the fact that firms devote more energy to large volume physicians or physicians that are more responsive to detailing (Manchanda et al. 2004). The prescriptions are modeled by a multivariate Poisson regression model with a full (co)variance matrix allowing for overdispersion, as in Chib and Winkelmann (2001). We extend their model by allowing for individual-specific variables. The probability of l prescriptions, Rx_{ijt}, for physician $i = 1...I$, brand $j = 1...J$ and month $t = 1...T$ is given by:

$$\Pr(Rx_{ijt} = l \mid v_{ijt}) = \left(\frac{\exp(-v_{ijt}) \cdot v_{ijt}^{l}}{l!} \right), \tag{1.2}$$

with v_{ijt} parameterized as

$$v_{ijt} = \exp\begin{bmatrix} \beta_{0ij} + \beta_{1ij} \ln(Det_{ijt} + 1) + \beta_{2ij} \ln(\sum_{k \neq j} Det_{ikt} + 1) + \\ \beta_{3ij} \ln(Rx_{ij,t-1} + 1) + \beta_{4ij} \ln(\sum_{k \neq j} Rx_{ik,t-1} + 1) + \\ \beta_{5ij} Trend + \beta_{6ij} Trend^{2} + \beta_{7i} IntroCrestor + \xi_{ijt} \end{bmatrix}, \tag{1.3}$$

$$\beta_{ij} \sim N(\mu_{\beta}^{j}, \Sigma_{\beta}^{j}), \quad \xi_{it} = \{\xi_{i1t} \ldots \xi_{iJt}\} \sim N_{J}(0, \Sigma_{\xi}). \tag{1.4}$$

Here v is the conditional mean that has to be positive, because we only observe positive outcomes of Rx. Det denotes the number of detailing visits (either own or competitive ones) received during the corresponding time period. To accommodate trending patterns and category growth, we include a linear-quadratic operationalization of the $Trend$ variable. ξ proxies for other variables that are observed by the physician but not by the researcher. These include but are not limited to: direct-to-consumer advertising (DTCA), symposium meetings and medical journal reading. The individual- and brand-specific β-parameters are distributed with brand-specific mean μ_{β}^{j} and a full within-brand covariance matrix Σ_{β}^{j}.

The parameter β_{0ij} is a physician- and brand-specific constant capturing all time-invariant factors influencing the physician's prescription behavior for a certain brand. This

parameter mainly reflects the physician's base preference for a brand, but can also subsume other factors like the size of the practice and the types of patients the respective physician treats. This base prescription level of a physician for a certain brand is likely to influence the detailing effort directed to that physician by pharmaceutical firms.

β_{1ij} is the physician's responsiveness to detailing for brand j, which is also likely to be correlated with the detailing activity of pharmaceutical firms toward a physician.[9] β_{2ij} measures the influence of competitive detailing, summed across all brands, on physicians' prescription behavior.[10] In order to accommodate carryover effects both in own and competing prescriptions, we include $\ln(Rx_{ij,t-1}+1)$ and $\ln(\sum_{k\neq j} Rx_{ik,t-1}+1)$ respectively as additional covariates. β_{3ij} reflects the own-brand carryover effect for physician *i* and β_{4ij} measures the carryover influence of the competitive prescriptions.

The trend variables β_{5ij} and β_{6ij} measure a physician- and brand-specific time trend to capture the dynamics caused by the introduction of Crestor, category expansion and other news affecting the drugs in the statins market. As Crestor was introduced at the start of our dataset, we also included the dummy *IntroCrestor,* which takes the value one for Crestor in the first month of our data and zero for all others observations.

To ensure that the omission of unobserved demand drivers does not alter our main results, we capture these effects mainly by the inclusion of full covariance matrices Σ_{β}^{j} and Σ_{ξ}. The latter captures the contemporaneous correlations between brands observed by the physicians and firms but not observed by the researcher.

To correct for the strategic behavior of firms concerning their detailing allocation per month, brand and physician, we specify an extra equation for detailing (supply) similar to Manchanda et al. (2004).[11] We model the number of detailing visits by a Poisson model:

$$\Pr(Det_{ijt}=m \mid w_{ijt}) = \left(\frac{\exp(-w_{ijt}) \cdot w_{ijt}^{m}}{m!} \right). \qquad (1.5)$$

Here the conditional mean *w* of Equation (1.5) is a function of the constant in the prescription equation β_{0ij}, the response coefficient β_{1ij} and competitive detailing:

[9] We use a log-log relation, which approximates a linear relationship between detailing and prescriptions. We have also specified a version of our model with detailing transformed to 1/(1+Det) to allow for decreasing marginal effects of detailing (see Dong et al. 2008). This transformation did not alter our results because physicians in our data usually receive less than two detailing visits per month.

[10] This model choice is driven by parsimony considerations. An extension that accommodates each competing brand separately is straightforward.

[11] Note, our detailing model does not assume any specific supply-side model of inter-firm conduct. Our detailing model simply accounts for non-random choice of detailing levels across physicians.

$$w_{ijt} = \exp\left[\begin{array}{l}\gamma_{0j} + \gamma_{1j}\dfrac{\beta_{0ij}}{1-\beta_{3ij}} + \gamma_{2j}\dfrac{\beta_{1ij}}{1-\beta_{3ij}} + \\ \gamma_{3j}\ln(\sum_{k\neq j} Det_{ik,t-1} + 1) + \varsigma_{ijt}\end{array}\right], \text{ for } j = 1...J. \qquad (1.6)$$

The response parameters β_{0ij} and β_{1ij} from the prescription response model are divided by $1-\beta_{3ij}$ to account for carryover effects. We can interpret these terms as the long-term coefficients of base prescription volume and detailing responsiveness. γ_{0j} reflects a brand's base detailing allocation, which we allow to differ across brands. γ_{1j} captures the influence of physicians' base prescription volume for brand j on the mean number of detailing visits for the same brand. γ_{2j} measures the influence of physicians' responsiveness to detailing of brand j and γ_{3j} the influence of competitive detailing visits from the last period. Note that in this extended version of the Manchanda et al. (2004) model, both the demand- and supply-equation include competitive activities, which is especially relevant when one considers a policy shift that likely changes the interactions between the market players. The error term ζ is assumed to have a normal distribution for brand $1...J$ and is uncorrelated with the demand-side error ξ. The demand and supply model in Equation (1.3) and (1.6) are however related to the common appearance of β_{0ij}, β_{1ij} and β_{3ij}. The complete estimation procedure, as specified above, is presented in Appendix 1B.

Supply Model on Stated Detailing Data

To estimate how competing firms reallocate their detailing after various policy shifts, we have to model the outcomes of the conjoint experiment. We separately model the allocation per brand and per scenario, which results in 18 scenarios, six for the two brands that do not initiate a policy shift and three for the two brands initiating a policy shift. Similar to the supply model on the revealed data, we make detailing a function of physicians' prescription volume, detailing responsiveness and competitive detailing. Because the respondents have diverse backgrounds and insights, we allow for heterogeneity in their parameters by estimating a hierarchical linear model with the average number of details as the dependent variable.

Results

Results of Demand and Supply Model on Observed Data

The results of the demand and supply model, estimated on our revealed prescription and detailing data for a sample of 1,585 physicians, are shown in Table 1.1. The first row of Table 1.1 shows the brand constants, which are proportional to the brands'

market shares. The (own) detailing effect is positive for all brands, which means that detailing calls positively influence the number of prescriptions a physician writes for the brand. The long-term effects of detailing can be approximated by dividing the detailing coefficient by one minus the carryover effect, $\beta_{1ij} / (1-\beta_{3ij})$. These long-term detailing effects are: 1.34 for Crestor, .32 for Lipitor, .37 for Pravachol and .60 for Zocor. The detailing effect for the recently introduced brand, Crestor, is much higher compared to the other brands. This is in line with the conclusions of Narayanan et al. (2005) that the detailing effect is greater in the early stages of the product life cycle.

The trend variables are scaled to be between zero and one. For Crestor we observe a positive trend and for the other brands we observe small trend coefficients, indicating almost no growth during the estimation period, which is supported by the monthly number of prescriptions we observe.

The carryover effects are positive for all brands, being the largest for Crestor (.57) and the smallest for Lipitor (.38). The competitive carry-over effects in prescriptions are slightly positive, ranging from .08 for Lipitor to .15 for Zocor. The competitive detailing effects are negative for all brands, but only significantly so for Crestor and Pravachol. The effect is largest for the new brand, Crestor, which seems to be more vulnerable. The reason may be that physicians' preference structure is more uncertain for new brands than mature brands.

For Crestor, we also estimate a negative introduction dummy of -.1.02. The reason is that Crestor was approved on the 12th of August 2003 and thus the first period contains sales of only half a month.

The covariance matrix shows that the variance/covariance is significantly positive between the incumbent brands. The covariance between Crestor and the incumbent brands is relatively large and negative, capturing switching behavior towards the new drug. While the competitive effects and long-term trend are already captured in the demand equation, the covariance captures the short-term variation in the market. The results of the covariance matrices Σ_{β}^{j} can be found in Appendix 1C, Table 1C.1 till 1C.4.

The estimates of the detailing model are given in the lower part of Table 1.1. The parameters indicate the strategic detailing behavior for the different brands. The constant indicates the base detailing level for all brands. Crestor shows the highest median value, -1.41. It is quite common to see higher detailing levels around the introduction of a new brand, as detailing is found to be most effective in the introduction stage (Narayanan et al. 2005; Neslin 2001; Osinga et al. 2010).

For all four brands, we find negative values for the parameter indicating the influence of physician's base prescription volume on the number of details received. Remember that the effect of base prescription volume is given by $\left(\gamma_{1j} \cdot \frac{\beta_{0ij}}{1-\beta_{3ij}}\right)$. Because the constant β_{0ij} is negative for all brands, a more negative value for γ_{1j} indicates a more positive influence of phycicians' prescription volume on the number of details they receive. The effect ranges from -.18 for Pravachol to -1.26 for Lipitor, in line with Manchanda et al. (2004).

The results also show that physicians receive more detailing calls as their responsiveness to detailing increases. This effect is significant for all brands, and largest for Lipitor (1.76). Manchanda et al. (2004) earlier found that physicians receive fewer detailing calls as their responsiveness to detailing increases. While recognizing the lack of logic in this finding, they attributed it to the absence of competitive detailing in their dataset. Our data and model contain such competitive detailing efforts and thereby obtain more intuitive estimates.

We also find that physicians receive more detailing calls as they receive an increasing number of competitive detailing calls (see Dong et al. (2009b) for a similar result). This effect is significant for the established brands Lipitor, Pravachol and Zocor, and the effect is largest for the last one, .37. Firms seem to mimic each others' detailing at the individual level. Such effects could start a vicious cycle, very much along the agurments of GSK's former CEO, Garnier, we cited at the start of this paper, and can lead to an overload of sales calls to physicians.

Results of the Stated Detailing Data

We start with some descriptive outcomes of our conjoint experiment. Compared to the base scenario, respondents changed the size of their sales force in 34% of the hypothetical market scenarios. In line with the competitive reactions literature (Leeflang and Wittink 1996; Steenkamp et al. 2005), respondents changed their sales force levels more often the larger the market share of the brand initiating the shift and the larger the size of the shift was. For example, when market leader Lipitor decreases its sales force by 40%, 61% of the respondents changed their sales force size, while a 10% sales force decrease of Pravachol only leads to a change in sales force size in 4% of the cases.

The respondents on average changed the allocation of their sales force in the hypothetical scenarios in 52% of the cases, compared to their allocation in the base scenario, indicating the importance of taking allocation into account instead of size only.

Again, we observe a pattern in which larger policy shifts induce more respondents to change their allocation.

Results of Data Enrichment

Before actually enriching the revealed data with the stated data, we test whether both datasets can be pooled. For every brand, we have estimated Equation (1.1) and allow in the first step for a non-one scaling factor. The results are shown in Table 1.2. For all brands, we cannot reject the null hypothesis of data pooling. Tests for a scaling factor equal to one cannot be confirmed. The resulting scale factors are given in Table 1.2 and are fairly consistent across brands.

As the scale factor applied to the stated data is smaller than one, the allocation of the conjoint respondents is more extreme towards the low and high levels of the physicians' attributes. A possible explanation is that in the stated data perfect targetability is assumed, while in reality there exists more uncertainty about the physician attributes.

Based on these test results, we can pool the data across datasets and given the consistency of the scaling factors across brands, we conclude that the conjoint data have face validity. Under the assumption that the preference structure across base and hypothetical scenarios are the same, we can now safely apply the recovered scaling factors to the hypothetical market scenarios.

We present the pooled estimates on the revealed and stated detailing data under the base scenario in Table 1.3. We obtain results that are similar to the estimates of the revealed preference model, as we find that high-volume physicians, detailing-responsive physicians and those who receive more competitive details, are detailed more than their counterparts that score low on these variables. For the last two variables we observe some evidence for nonlinearity. Table 1C.5 shows the estimations of the detailing allocation under all six hypothetical market scenarios, corrected by the firm-specific scale factor. These estimations are used in the market simulations to compute the detailing allocations after the policy shifts.

Table 1.4 provides the outcomes of the market simulations after enriching the revealed data with the stated data under the different conjoint scenarios. It shows for each of the six hypothetical market scenarios the differences between the situation before and after the policy shift. The fourth column shows the relative change in details, the fifth column the relative change in prescriptions and column six gives the absolute change in market share. The absolute change in profit margin is given in the seventh column and the last column shows the relative change in market size. The absolute changes are calculated by: *new value – old value*; the relative changes are calculated by: *(new value – old value) /*

old value. As an example, the first row considers the implications for Crestor after a 10% decrease in detailing of Lipitor. This leads to a sales force increase for Crestor of 2.77%, an increase in prescriptions of 2.58% and a change in the market size of -.58%. The market share of Crestor increases .38 percentage points and its profit margin decreases .30 percentage points. We calculated profit margins based on the costs of a detailing visit and the revenues of prescriptions. We use a value of $150 for the cost (all-in, except samples) of an average detailing call, based on company records of Quintiles Transnational Corporation, the largest provider of pharmaceutical sales services. We use values of $70 for Crestor, $90 for Lipitor, $80 for Pravachol and $100 for Zocor, for the revenue of a single prescription, based on data from IMS Health and Consumer Reports[12]. We do not subtract a manufacturing cost, which is not available to us, but, at the same time, known to be very small.

Table 1.4 leads to the following conclusions. First, it makes a big difference whether Lipitor or Pravachol initiate the policy shift. While a decrease in detailing for market leader Lipitor often triggers competitors to also decrease their sales force, a decrease in detailing for Pravachol typically triggers competitors more often to increase the number of detailing calls.

Second, there is only one scenario that is beneficial for all four companies. When market leader Lipitor decreases its sales force by 40%, it will increase its profit margin by 8.52%, while Crestor (12.62%), Pravachol (2.33%), and Zocor (7.00%) also all increase their profit margin.

Third, for every policy shift the initiator increased its profit margin. This finding can be seen as evidence for 'overdetailing' in this therapeutic category (see also Montoya et al. 2009). The profits of competitors (e.g. Crestor) can either increase or decrease.

Fourth, all downward policy shifts in detailing lead to a smaller category size ranging from a decrease of .58% when Lipitor lowers detailing by 10%, to a market-size decrease of 4.41% when Lipitor decreases its sales force by 40%. This finding shows that total market size of a category can shrink as a consequence of one brand reducing its detailing, but possibly only so when the detailing decrease is large enough. The latter part may explain the contrast between our findings and the findings of Narayanan et al. (2004), on a dataset with more limited variation in detailing supply.

[12] IMS Midas price system and Consumer Reports best buy drugs: The Statin Drugs (January 2006).

Validation

We internally validate our results by conducting various robustness checks on the demand-supply model and the model for the conjoint-derived outcomes. We have tested for a marginally decreasing effect of detailing in Equation (1.3) by transforming the detailing to *1/(1 + Det)*, as is done in Dong et al. (2009a). We also considered different forms for the trend terms and tested whether they are equal across brands. The robustness of the detailing equation is tested by including a lagged versus a contemporaneous effect of competitive detailing. We have estimated a model where we dropped the carryover effect from Equation (1.6). All these changes did not change our four main results substantially, which strengthens the confidence in our results. The results are available from the authors upon request.

Concerning our market simulations, we recognize that our results are subject to the cost and revenue figures chosen. Therefore we run a sensitivity analysis for the scenario in which Lipitor decreases its sales force by 40%. We calculate the profit margin change under a low and high estimate for the cost of detailing, $100 and $200 respectively, and a low (20% lower) and high (20% higher) revenue per prescription. Table 1.5 shows that the outcomes are robust to the chosen numbers and that only the levels of the outcomes shift.

For external validation, we distinguish between outcomes obtained by merely extrapolating outside the data range, but within the policies observed in the data, and extrapolating beyond the policies observed in the data. As our goal is to gauge the outcomes of a policy shifts before initiation we do not observe the actual outcomes of the shift and therefore we resort to alternative ways of validation.

A 10% decrease in detailing can reasonably be considered as a form of data extrapolation. Hence, we compare the outcomes obtained with data enrichment to the outcomes without enriching the data. We do this by applying a single shock to the demand- and supply system in Equations (1.2)-(1.6). For the 10% decrease in detailing for Pravachol and Lipitor detailing decreases now for every firm, but the outcomes in terms of profits are mixed, similar to our main results. If we simulate a 40% sales force reduction of Lipitor without enriching the data, we obtain lower detailing levels for all companies, but mixed changes in profit margins. Compared to the main results, the detailing decreases for the followers are much smaller. We can also compare the outcomes with Berndt et al. (2003), who consider a detailing change of similar size, i.e. a 10% increase for all market players in the H2-antagonist antiulcer drugs category. They find mixed results in terms of profits across drugs and profit changes in a similar range as we find.

We identify four relevant external validation approaches, to validate the outcomes outside the policies observed in our data. First, the outcomes are validated by comparing them to the academic literature. Second, outcomes are compared with another policy shift in the pharmaceutical industry. Third, the outcomes are compared with similar situations in other industries. Fourth, the results are shown to a set of experts for evaluation.

The academic literature supports our findings. The competitive reactions literature agrees that a larger policy shift elicits stronger competitive reactions, (e.g. Leeflang and Wittink 1996; Steenkamp et al. 2005). Furthermore, mainly big firms are able to change the norms of competitive conduct in the market (Scherer and Ross 1990). This is exactly what we find in our results where only a 40% decrease in detailing of market leader (and biggest pharmaceutical firm) Pfizer, triggers substantial and aligned competitive reactions. This policy shift likely changes the rules of competitive interaction (Thomas and Soldow 1988).

In the pharmaceutical market, firms signaled that the detailing arms race should be ended, and although it did not have an immediate effect, Pfizer announced on November 28, 2006 a large sales force cut (New York Times 2006a). Also fueled by two major patent expiries in the statins category earlier that year, detailing in the statins category decreased that same quarter by almost 15%, and the firms aligned their detailing decreases (ranging from 6 to 19%) similar to what we observe for the scenario in which Lipitor decreases its detailing by 40%.

Comparing our results to other industries yields many similar solutions to end an arms race as we identified above. Arms races in the airline industry, cigarette industry, gasoline market, retailing, shaving industry and telecommunications have all come to an end at a certain point and some of them have done that by initiating a policy shift. The examples of P&G (Ailawadi et al. 2001; Ailawadi et al. 2005) and Philip Morris (Chen et al. 2009) are compelling examples of the effectiveness of a policy shift. They also show that a large shift by the market leader (in the cigarette industry, Philip Morris initiated a price shift of 20%) is able to buck the trend and set new competitive market conduct.

We have also done a convenience survey among a new set of pharmaceutical managers to shed light on the results of our research. The main question was “If you agree that there is an arms race in the pharmaceutical industry, why is there no market leader that ends the arms race by making a major reduction in sales forces?” 92% agrees that there is/was an arms race in the pharmaceutical industry. Answers can be categorized into M&A solutions, sales force reductions due to other factors such as patent expiries, and risk aversion: ‘too risky to miss out any opportunity in the market’ and ‘no company wants to be the first to withdraw troops from the battlefield.’ They also recognized that some firms

have already been decreasing their sales forces. In general, these responses show much similarity to the lack of strategic competitive reasoning reported in Montgomery et al. (2005).

Discussion

In this paper, we gauge the consequences of a downward, firm-initiated policy shift in pharmaceutical detailing. The results indicate first that a large policy shift of the market leader (a 40% decrease in the sales force of Lipitor) was the only shift that was profitable for all firms in the market. This seems to explain part of the arms race in sales forces, where small changes in the sales force are apparently not able to buck the trend in a profitable way and a drastic reduction of the sales force of the market leader is needed. Second, the policy shift initiator always increased its profit margin by decreasing its sales force, while its competitors' profits may both increase and decrease after the policy shift. Third, all downward policy shifts in detailing we consider lead to a decrease in category size.

We also provide an alternative decision support tool for firms and public policy makers to gauge the firm-level consequences of large policy shifts, taking into account their impact on demand and competitive response. We use stated detailing data (obtained through a conjoint experiment) to complement past panel data on prescriptions and detailing. The idea behind our method can be extended to gauge any kind of policy shift before it is initiated, if the researcher collects additional data on the parameters that cannot be generalized beyond the policy observed in the data. The tradeoff for the researcher is how the costs of additional data collection compare to an experiment in a test market, and whether it offsets the limitations of the readily available data and methods.

Implications for Managers and Public Policy

Our approach and findings have several implications for managers and public policy. First, we show that only a large downward detailing policy shift by the market leader can buck the trend in pharmaceutical detailing in the entire category. Pharmaceutical companies share concern about how their industry is viewed by care providers, government and society at large. Excessive physician detailing is one main reason for the negative perceptions among these stakeholders. Our results provide support for market leaders to take their responsibility in curtailing detailing, as only they have the visibility needed to curb detailing levels in the entire category. If market leaders do not take their responsibility, governments should consider intervention by means of 'soft coordination' or by restricting detailing by law. Several states in the U.S. have already implemented laws

restricting pharmaceutical marketing and the U.S. government can also learn from the regulations across the world (see Stremersch and Lemmens 2009).

Second, our results show that for many pharmaceutical firms reducing their detailing to physicians would be a profit-enhancing strategy. While considered by many firms, very few firms greatly reduced their detailing efforts. Our findings show that profit-maximizing firms should reduce their sales forces. As lower profits imply lower R&D expenditures, government might also consider intervention.

Third, we find that category size decreased with a downward policy shift in detailing. This finding can inform the public policy debate on the public health effects of detailing, as it shows that detailing does not only affect the market share of drugs within the category but also overall prescriptions in the category. Depending upon public policy's goals, whether cost reduction or drug access enhancement, policy makers may consider curtailing detailing efforts of manufacturers.

The literature has identified different routes to buck the trend in an arms race: (1) coordination among competitors (e.g. by information sharing), (2) setting a new market conduct by initiating a policy shift, (3) a firm-initiated change in the market structure, such as radical new product introduction or mergers and acquisitions, and (4) regulatory changes. If firms are in an undesirable market state, coordination within legal bounds is the first solution considered. This can be achieved by an external party like the government, another interest group, or the firms themselves. Firms often spread their opinions and hint on possible actions, called signaling. Signals are then often followed by an action of one of the market players. The government or other interest groups can have an interest in disseminating information to the market that can trigger companies or industries to change their practice or they can just negotiate directly with the relevant market players to obtain a more favorable market outcome. Setting a new market conduct by changing your own policy can also be a successful but risky way to buck the trend. Another possibility to buck the trend is to change the market structure, which partly explains the recent spur in mergers and acquisitions in the pharmaceutical industry, which was also mentioned by the managers involved in our study as a possible solution to the arms race. Finally, the government could consider interfering in a market with regulations. The U.S. federal government has not done much so far, which triggered the states to design their own regulations, restricting pharmaceutical marketing (Huffington Post 2008), such as compulsory licensing for detailers in D.C., restrictions in physician data (e.g. New Hampshire), prohibition of gifts (e.g. Vermont) and counterdetailing (e.g. Pennsylvania).

Finally, the data enrichment methodology we develop can gauge the likely consequences of policy shifts ex ante. Whereas advanced econometric methods often

perform well in forecasting, managers tend not to accept these black boxes to base their decisions on (Little 1970). Our method can add to the use of sound quantitative methods to make important decisions, as it makes use of a standard demand-and-supply model and conjoint analysis that organizations are increasingly more familiar with. In case of the pharmaceutical industry, the different interest groups can use our approach as a coordination tool. Federal and state governments can use it as a 'soft coordination' tool to convince companies to scale down their detailing. For other interest groups like PhRMA (a trade group representing the pharmaceutical companies), the American College of Physicians (ACP) and the American Medical Association (AMA) it can also be very helpful to gauge the consequences of hypothetical policy shifts.

Limitations and Future Research

As with any new research endeavor, while much ground has been covered, much work remains. First, we do not consider all of the firms' marketing efforts, restricting our model to detailing for simplicity. While marketing budgets are set across marketing instruments, it is unlikely that the targeting of these other instruments is in direct accordance to the detailing allocation within the same time frame. Direct-to-consumer advertising (DTCA) and journal advertising reach the physician in completely different ways than detailing. DTCA reaches the physicians via patients and journal advertising is based on physician reading behavior. Meetings are more likely to be set in accordance with detailing. However, meeting expenditures are relatively small (one-fifth of the detailing expenditures, see Donohue et al. 2007). And, moreover, they are often organized around special events of a drug, such as the approval of a new dosage or a new drug form. Thus, while the absence of other marketing instruments limits our insights, it may not yield any bias in the insights we gain on detailing.

Second, we acknowledge that firms also allocate their sales reps across their products, so downsizing the sales force for a brand in one therapeutic category can affect the other brands of the firm. Such effects are not captured by the present study.

A third limitation is that we consider the firm-initiated policy shift as fixed as the firm is not allowed to react to competitive reactions following its initiation. In reality, a large policy shift can involve different rounds with multiple competitive reactions such as in the Dutch retail price war (Van Heerde et al. 2008). The policy shift of Philip Morris (Chen et al. 2009), on the other hand, involved only one round. Philip Morris changed the prices of its products and after two to three months, the competitors followed suit. Studies extending our research to multiple-round interactions between firms seem valuable.

A fourth limitation is that the predictive validity of our conclusions hinges on the accuracy of conjoint respondents' assessment of competitive responses to the initiated policy shift. While we have taken great care in key informant selection and the data we obtained from the conjoint experiment displays high face validity, given the results we presented before, our core argument is not that enriching conjoint data from key informants with revealed data delivers perfect forecasts. Rather, we show how such stated key informant data – as an imperfect guesstimate on future competitive reactions – can be consistently combined with revealed data to gauge the consequences of policy shifts.

Future research can also fruitfully extend our present paper in other ways. Ideally, one compares the forecasts from our data enrichment method with a real future policy shift to evaluate the external predictive validity. It would also be valuable to test the strength of conjoint analysis to decompose hypothetical market scenarios into different attributes. Our current approach gauges the consequences of policy shifts that are determined upfront. A delineation of policy shifts in conjoint attributes and levels would allow the researcher to consider a much wider range of policy shifts.

Tables

Table 1.1: Parameter Estimates for Revealed Prescription and Detailing Model

Prescription Model	Crestor	Lipitor	Pravachol	Zocor
Constant	-1.11 (-1.49,-.80)	-.28 (-.40,-.15)	-1.68 (-2.30,-1.16)	-.50 (-.62,-.35)
Ln(Own Detailing)	.58 (.54,.65)	.23 (.16,.31)	.19 (.12,.26)	.32 (.28,.36)
Ln(Competitive Detailing)	-.34 (-.44,-.22)	-.01 (-.07,.09)	-.09 (-.12,-.07)	-.03 (-.10,.02)
Ln(Own Prescriptions (t-1))	.57 (.54,.61)	.38 (.36,.41)	.48 (.45,.51)	.47 (.44,.50)
Ln(Competitive Prescriptions (t-1))	.11 (.07,.15)	.08 (.06,.10)	.09 (-.01,.17)	.15 (.10,.19)
Trend	.44 (.36,.53)	.09 (.07,.11)	-.01 (-.03,.00)	.07 (.06,.09)
Trend squared	-.35 (-.43,-.30)	-.03 (-.04,-.01)	.01 (.00,.02)	-.07 (-.08,-.06)
Introduction Dummy	-1.02 (-1.17,-.86)			
Covariance				
Crestor	.28 (.20,.36)	-.53 (-.69,-.41)	-.17 (-.22,-.13)	-.34 (-.43,-.26)
Lipitor	-.53 (-.69,-.41)	1.07 (.78,1.38)	.33 (.24,.42)	.66 (.47,.85)
Pravachol	-.17 (-.22,-.13)	.33 (.24,.42)	.12 (.09,.15)	.20 (.15,.26)
Zocor	-.34 (-.43,-.26)	.66 (.47,.85)	.20 (.15,.26)	.45 (.33,.58)
Detailing Model				
Constant	-1.41 (-1.87, -1.17)	-1.67 (-1.84, -1.29)	-2.13 (-2.46, -1.96)	-1.60 (-1.87, -1.40)
Rx Volume	-.41 (-.71, -.17)	-1.26 (-1.51, -.69)	-.18 (-.44, -.03)	-.63 (-.75, -.44)
Responsiveness	.64 (.42, .90)	1.76 (1.41, 2.47)	.88 (.63, 1.13)	.74 (.54, 1.16)
Ln(Competitive Detailing (t-1))	.19 (-.04, .32)	.24 (.13, .31)	.35 (.29, .42)	.37 (.31, .41)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 1.2: Data Can Be Pooled Up to a Non-One Scale Factor

	Chow Test Statistic with Scale Factor	Scale Factor
Crestor	.74	.38
Lipitor	1.56	.57
Pravachol	1.48	.52
Zocor	1.24	.31

Note: The critical value is 1.72 based on an α of .1.

Table 1.3: Pooled Estimates of the Detailing Model, Based on Revealed and Stated Detailing Data (95% confidence interval in brackets).

		Crestor		Lipitor		Pravachol		Zocor	
Constant		.10	(.05, .14)	.18	(.13, .22)	-.03	(-.06, .01)	.33	(.26, .40)
Prescription Volume	Low	-.17	(-.20, -.11)	-.19	(-.25, -.10)	-.07	(-.13, -.03)	-.07	(-.11, -.02)
	Mid	-.10	(-.14, -.05)	-.07	(-.11, -.02)	-.04	(-.09, .01)	-.05	(-.10, .00)
	High	.27	(.21, .34)	.26	(.18, .33)	.11	(.06, .17)	.12	(.07, .20)
Responsiveness to Detailing	Low	-.09	(-.12, -.06)	-.04	(-.09, .00)	-.06	(-.11, -.01)	-.06	(.-10, .01)
	Mid	.02	(-.02, .05)	-.04	(-.07, .00)	-.03	(-.06, .01)	-.02	(-.05, .02)
	High	.07	(.03, .11)	.08	(.01, .12)	.09	(.04, .12)	.08	(.02, .12)
Competitive Detailing Levels	Low	.00	(-.04, .04)	-.02	(-.06, .03)	-.03	(-.06, .00)	-.04	(-.06, -.02)
	Mid	-.03	(-.06, .00)	-.04	(-.07, .01)	-.02	(-.06, .00)	-.01	(-.04, .02)
	High	.03	(-.01, .07)	.06	(.01, .09)	.05	(.01, .09)	.05	(.02, .09)

Note: The results are estimated using effects coding.

Table 1.4: Outcome Measures after the Policy Shifts

		Market Changes after Policy Shift					
Shift in Detailing	**Shift Initiator**	**Company**	**Details**	**Prescriptions**	**Market Share**	**Profit Margin**	**Market Size**
-10%	Lipitor	Crestor	2.77%	2.58%	.38%	-.30%	-.58%
		Lipitor	-10.00%	-3.87%	-1.53%	1.73%	
		Pravachol	-.24%	-4.14%	-.50%	-1.82%	
		Zocor	-3.65%	5.29%	1.65%	3.60%	
-25%	Lipitor	Crestor	1.02%	.48%	.34%	-.90%	-2.36%
		Lipitor	-25.00%	-4.14%	-.84%	5.37%	
		Pravachol	-1.02%	-2.64%	-.04%	-.75%	
		Zocor	-6.75%	-.47%	.54%	2.67%	
-40%	Lipitor	Crestor	-9.12%	-1.70%	.34%	12.62%	-4.41%
		Lipitor	-40.00%	-7.63%	-1.56%	8.52%	
		Pravachol	-8.87%	-3.86%	.08%	2.33%	
		Zocor	-16.95%	-.50%	1.14%	7.00%	
-10%	Pravachol	Crestor	-.76%	-.93%	.02%	-.30%	-1.06%
		Lipitor	3.92%	-2.09%	-.48%	-1.47%	
		Pravachol	-10.00%	1.83%	.41%	4.73%	
		Zocor	-5.87%	-.85%	.06%	2.15%	
-25%	Pravachol	Crestor	16.68%	2.78%	.46%	-22.64%	-1.02%
		Lipitor	-5.33%	-3.63%	-1.22%	.42%	
		Pravachol	-25.00%	-1.46%	-.06%	1.29%	
		Zocor	6.09%	1.90%	.83%	-1.74%	
-40%	Pravachol	Crestor	18.58%	-.49%	.04%	-32.09%	-.86%
		Lipitor	3.65%	-2.09%	-.57%	-1.40%	
		Pravachol	-40.00%	-3.84%	-.42%	16.51%	
		Zocor	4.13%	2.49%	.95%	-.68%	

Note: The differences for details and prescriptions and market size are relative differences (new outcome – old outcome)/(old outcome). While the market share and profit margins are differences in share points (new percentage – old percentage).

Table 1.5: The Main Results Are Stable to Changes in Detail Costs and Revenues per Prescription

		Profit Margin Change after Policy Shift			
Policy shift	**Company**	**Revenues -20% Detail costs 100**	**Revenues -20% Detail costs 200**	**Revenues +20% Detail costs 100**	**Revenues +20% Detail costs 200**
Lipitor -40%	Crestor	1.52%	21.04%	7.01%	14.02%
	Lipitor	7.10%	14.20%	4.73%	9.47%
	Pravachol	1.95%	3.89%	1.30%	2.59%
	Zocor	5.83%	11.67%	3.89%	7.78%

Appendix 1A

Here we provide the instructions for the conjoint experiment we conducted. Participants were shown the following introduction.

"In the United States, physicians – both specialists and general practitioners – are often visited by representatives from pharmaceutical companies. These so-called sales reps are detailing the products of their company to the physicians.

In this questionnaire, some scenarios of the pharmaceutical market are posed. You are asked to consider yourself as the decision maker concerning the size and allocation of the sales force in the different scenarios presented below.

Background information:

When firms consider strategic decisions concerning the size and allocation of their sales force, not only the costs and responsiveness of the physicians play a role. Reducing the sales force substantially brings along other problems. Firms have to deal with the people who lose their job often with generous severance packages. Those people carry intimate company knowledge with them and are (especially in the pharmaceutical industry) potential whistleblowers, which have cost the pharmaceutical industry enormous amounts of money.

Increasing the sales force also brings some practical issues, such as the recruitment of suitable sales reps and their training."

Although the respondents all indicated that they were familiar with the allocation and size of the sales force, we presented them with both the benefits and downsides of increasing or decreasing the sales force to place the respondents in the desired decision environment (information acceleration). Next the respondents were shown an example page to become familiar with the conjoint tasks.

"Below is an example of the tasks to perform in the rest of the questionnaire. Each time you have to act as one firm in the market. You are asked to make decisions in three different environments. Each environment contains one allocation task for the current market situation and then 3 general reactions and allocation questions after a policy shift of one of the competitive firms in the market.

Imagine you are in the following situation of the U.S. market of statin drugs: (see Table 1A.1)

The firm for which you have to decide is shaded gray. The allocation concerns 100 sales visits, which have to be divided among 4 different types of physicians."

Then the respondents were presented with 12 different allocation questions. They started with a base scenario mimicking the situation in the panel data (see Figure 1A.1). This was followed by three market scenarios, where one of the competing firms decreased the sales force. In those scenarios, the respondents were also asked how they would react with the size of the sales force (see Figure 1A.2).

Table 1A.1: The Market Situation Shown to Conjoint Respondents

Company	Drug	Goes off Patent in	Market Share
Pfizer	Lipitor	5 years	40%
Merck	Zocor	2 years	20%
AstraZeneca	Crestor	2 years	10%
Bristol-Myers Squibb	Pravachol	13 years	5%

Note: The market share is the share that the drug of a firm has in the statins market (based on information in our panel data and in IMS Health aggregate-level data).

Figure 1A.1: Example of a Conjoint Task under the *Base Scenario*

Environment 1

Below the physician types are defined on 3 characteristics:

1) Their prescription volume for the drug of your firm in the quarter before the policy shift.
2) Their responsiveness to detailing visits.
3) The number of competitive detailing visits they received in the last quarter.

QUESTION:

How would you divide the sales force for **BMS's Pravachol** under the current market situation (as in the table above)?
Divide 100 visits among the following 4 physician types.

	Prescription volume (number last quarter)	Responsiveness to detailing	Competitive detailing (number last quarter)	# of visits of **BMS** in **current market**
Type 1	Middle (4)	High	High (5)	
Type 2	High (6)	Middle	Middle (3)	
Type 3	Middle (4)	Low	Middle (3)	
Type 4	High (6)	Low	Low (1)	
				= 100

Figure 1A.2: Example of a Conjoint Task under a *Policy Shift Scenario*

Environment 1, Scenario 1

Imagine that **Pfizer decides to cut back** its sales force by **25 percent:**

How would **BMS** react for its brand **Pravachol**? Keep in mind that **the other competitors are also likely to react at the same time**. Pick one of the following answers and specify the change in sales force:

- ☐ We (BMS) would decrease our sales force for statins with . . . . . percent.
- ☐ We (BMS) would not react.
- ☐ We (BMS) would increase our sales force for statins with . . . . . percent.

Divide 100 visits among the following physician types after Pfizer has cut back its sales force for Lipitor by 25 percent:

	Characteristics **before** policy shifty			# of visits of BMS **after** sales force cut
	Prescription volume (number last quarter)	Responsiveness to detailing	Competitive detailing (number last quarter)	
Type 1	Middle (4)	High	High (5)	
Type 2	High (6)	Middle	Middle (3)	
Type 3	Middle (4)	Low	Middle (3)	
Type 4	High (6)	Low	Low (1)	
				= 100

Appendix 1B

All parameters for our demand-supply model (Equations 1.2-1.6) are estimated using the sampling scheme below. The sampler ran for 40,000 iterations with the first 20,000 discarded for burn-in. The prior structure for each β_{ij} is specified by

$$\beta_{ij} = \delta_j + \eta_{ij}, \tag{1B.1}$$

with δ_j a parameter vector, of *1* by *K*, to estimate, and $\eta_{ij} \sim N_k(0,\Sigma_{\eta,j})$, for $j = 1...J$. The prior parameters are distributed as follows.

$$\underline{\Sigma_{\xi}} \sim IW(r_0, R_0), \tag{1B.2}$$

$$\underline{\Delta_j} \mid \underline{\Sigma_{\eta,j}} \sim N(\Delta_0, \underline{\Sigma_{\eta,j}} \otimes A^{-1}), \quad \text{for } j = 1...J. \tag{1B.3}$$

$$\underline{\Sigma_{\eta,j}} \sim IW(r_{\eta 0}, R_{\eta 0}), \qquad \text{for } j = 1...J. \tag{1B.4}$$

$$\underline{\gamma_j} \sim N(\gamma_0, \Sigma_{\gamma}), \qquad \text{for } j = 1...J. \tag{1B.5}$$

with known hyperparameters r_0, R_0, Δ_0, A, $r_{\eta 0}$, $R_{\eta 0}$, γ_0, Σ_{γ} and $IW(\cdot,\cdot)$ an Inverted Wishart distribution with *r* degrees of freedom and scale matrix *R*.

We employed diffuse but proper priors with hyperparameters: $r_0 = 7$, $R_0 = r_0 \cdot I$, $\Delta_0 = 0$, $A = I$, $r_{\eta 0} = 10$, $R_{\eta 0} = r_{\eta 0} \cdot I$, $\gamma_0 = 0$, $\Sigma_{\gamma} = I$, where *I* refers to the identity matrix of the appropriate size.

The complete data likelihood for individual *i* is defined as follows:

$$p(Rx_i, Det_i, \beta_{ij}, \xi_{ijt}, \gamma_j \mid \Sigma_{\xi}, \Delta_j, \Sigma_{\eta,j}) = \prod_{j,t} \frac{f(Rx_{ijt} \mid Det_{ijt}, \beta_{ij}, \gamma_j, \xi_{ijt}) \cdot}{f(Det_{ijt} \mid \beta_{ij}, \gamma_j)}, \tag{1B.6}$$

with $f(Rx_{ijt}|\cdot) = Poisson(Rx_{ijt})$ and $f(Det_{ijt}|\cdot) = Poisson(Det_{ijt})$.

Multiplying the likelihood now with the prior gives the posterior for the complete data

$$\begin{aligned} &p(\beta_{ij}, \xi_{ijt}, \overline{\Sigma_{\xi}}, \overline{\Delta_j}, \overline{\Sigma_{\eta,j}}, \overline{\gamma_j} \mid \underline{\Sigma_{\xi}}, \underline{\Delta_j}, \underline{\Sigma_{\eta}}, \underline{\gamma}) \propto \\ &\left\{\underline{\Sigma_{\xi}} \sim IW(r_0, R_0)\right\} \cdot \prod_j \left\{\underline{\gamma_j} \sim N(\gamma_0, \Sigma_{\gamma})\right\} \cdot \left\{\underline{\Delta_j} \sim N_K(\Delta_0, \underline{\Sigma_{\eta,j}}, A)\right\} \\ &\cdot \left\{\underline{\Sigma_{\eta,j}} \sim IW(r_{\eta 0}, R_{\eta 0})\right\} \cdot \prod_i p(Rx_i, Det_i \beta_{ij}, \xi_{ijt}, \gamma_j \mid \Sigma_{\xi}, \Delta_j, \Sigma_{\eta,j}), \end{aligned} \tag{1B.7}$$

where we denote the priors with a bar below and the posterior with a bar above to distinguish both. We simulate from this distribution by sampling six parameter blocks using their conditional distributions.

Step 1: The latent error term ξ_{ijt} can be drawn conditional on the betas and the posterior covariance matrix $\overline{\Sigma_\xi}$ by using a Metropolis-Hastings step. The log conditional posterior density kernel for ξ_{it} is given by:

$$\ln \pi(\xi_{it} \mid \beta_{ij}, \overline{\Sigma_\xi}, v_{ijt}) \propto \sum_j \left(- v_{ijt} + Rx_{ijt} \ln(v_{ijt})\right) - 0.5 \xi_{it} \overline{\Sigma_\xi^{-1}} \xi_{it}', \tag{1B.8}$$

whereby a new candidate $\pi(\xi_{it}^c)$ is accepted with probability

$$\alpha = \min\left\{1, \pi(\xi_{it}^c) / \pi(\xi_{it}^{(-1)}\right\} \tag{1B.9}$$

and otherwise the draw of the previous iteration $\pi(\xi_{it}^{(-1)})$ is kept.

Step 2: In the second step, the individual- and brand-specific parameters β_{ij} are sampled.[13] We can see Equation (1B.1) as the prior for β_{ij}. The posterior is also influenced by Equation (1.2) and (1.5) and the posterior for β_{ij} is sampled by a Metropolis-Hastings step having the following log conditional posterior density kernel:

$$\begin{aligned} \ln \pi(\beta_{ij} \mid \overline{\Delta_j}, \overline{\Sigma_{\eta,j}}, w_{ijt}, v_{ijt}) \propto & \sum_t \left(- v_{ijt} + Rx_{ijt} \ln(v_{ijt})\right) + \\ & \sum_t \left(- w_{ijt} + Det_{ijt} \log(w_{ijt})\right) - \\ & 0.5(\beta_{ij} - \overline{\Delta_j})' \overline{\Sigma_{\eta,j}^{-1}} (\beta_{ij} - \overline{\Delta_j}). \end{aligned} \tag{1B.10}$$

Step 3: Then we can sample $\overline{\Sigma_\xi}$ from an inverted Wishart distribution by conditioning on the β's and the latent errors ξ:

$$\overline{\Sigma_\xi} \Big| \beta_{ij}, \xi_{ijt} \sim IW(r_0 + N \cdot T, R_0 + \sum_{i,t} \xi_{it}' \xi_{it}). \tag{1B.11}$$

Step 4: Now the matrices $\overline{\Delta_j}$ are sampled conditional on the β's from step 1 and the covariance matrix $\overline{\Sigma_{\eta,j}}$. Conditional on these parameters, this simplifies to a multivariate

[13] For notational simplicity we have not distinguished here between the β_{ij} that differ over brands and the β_i that are equal across brands.

regression model of which the conditional distribution is drawn by using the Gibbs algorithm:

$$\overline{\Delta_j}\left|\overline{\Sigma_{\eta j}}, \beta_{ij} \sim N((\sum_i z_i' z_i + A)^{-1}(z_i \beta_{ij} + A\Delta_0), \overline{\Sigma_{\eta,j}} \otimes (\sum_i z_i' z_i + A)^{-1}\right), \quad (1B.12)$$

where in our case z is a vector consisting of ones.

Step 5: This step samples the covariance matrices of the second layer of the model conditional on the individual β-parameters and the posterior parameters for the individual characteristics $\overline{\Delta_j}$. Just as in step 4, we can easily draw the covariance using a multivariate regression model.

$$\overline{\Sigma_{\eta,j}}\left|\overline{\Delta}_j, \beta_{ij} \sim IW(r_{\eta 0} + N, R_{\eta 0} + S_{\eta,j}).\right. \quad (1B.13)$$

Here S_η is given by

$$S_{\eta,j} = \sum_i (\beta_{ij} - \overline{\Delta}_j)'(\beta_{ij} - \overline{\Delta}_j) + (\overline{\Delta_j} - \Delta_0)' A (\overline{\Delta_j} - \Delta_0). \quad (1B.14)$$

Step 6: This step samples the γ-parameters by using the Metropolis-Hastings algorithm, where the log conditional posterior density kernel is given by:

$$\ln \pi(\overline{\gamma_j} \mid \beta_{ij}) \propto \sum_{i,t} \left\{ Det_{ijt} \beta_{ij} \overline{\gamma_j} - \exp(\beta_{ij} \overline{\gamma_j}) \right\} - 0.5(\overline{\gamma_j} - \gamma_0)' \Sigma_\gamma (\overline{\gamma_j} - \gamma_0). \quad (1B.15)$$

Appendix 1C

Table 1C.1: Covariance of the Demand Parameters for Crestor

	Constant	Detailing	Competitive Detailing	Own Prescriptions	Competitive Prescriptions	Trend	Trend squared	Introduction Dummy
Constant	.05 (.04,.07)	.02 (.01,.04)	.01 (.00,.02)	.01 (.01,.03)	.00 (-.01,.01)	.00 (-.01,.00)	.00 (-.01,.00)	.00 (.00,.01)
Own Detailing	.02 (.01,.04)	.05 (.03,.06)	.01 (.00,.02)	.01 (.00,.02)	-.02 (-.03,-.01)	-.01 (-.01,.00)	.00 (-.01,.01)	-.01 (-.02,-.01)
Competitive Detailing	.01 (.00,.02)	.01 (.00,.02)	.03 (.02,.04)	.01 (.00,.02)	-.01 (.00,-.02)	.00 (.00,.01)	-.01 (-.01,-.02)	.00 (.00,.00)
Own Prescriptions	.01 (.01,.03)	.01 (.00,.02)	.01 (.00,.02)	.04 (.02,.05)	.00 (.00,-.02)	.00 (-.01,.00)	.00 (-.01,.00)	.01 (.00,.01)
Competitive Prescriptions	.00 (-.01,.01)	-.02 (-.03,-.01)	-.01 (.00,-.02)	.00 (.00,-.02)	.04 (.02,.05)	.01 (-.01,.01)	-.01 (-.01,.00)	.00 (.00,.00)
Trend	.00 (-.01,.00)	-.01 (-.01,.00)	.00 (.00,.01)	.00 (-.01,.00)	.01 (-.01,.01)	.04 (.03,.04)	-.02 (-.02,-.01)	.00 (.00,.01)
Trend squared	.00 (-.01,.00)	.00 (-.01,.01)	-.01 (-.01,-.02)	.00 (-.01,.00)	-.01 (-.01,.00)	-.02 (-.02,-.01)	.03 (.03,.05)	.00 (-.01,.01)
Introduction Dummy	.00 (.00,.01)	-.01 (-.02,-.01)	.00 (.00,.00)	.01 (.00,.01)	.00 (.00,.00)	.00 (.00,.01)	.00 (-.01,.01)	.02 (.02,.03)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 1C.2: Covariance of the Demand Parameters of Lipitor

	Constant	Detailing	Competitive Detailing	Own Prescriptions	Competitive Prescriptions	Trend	Trend squared
Constant	.14 (.12,.17)	.02 (.01,.04)	.00 (.00,.02)	.01 (.01,.02)	.00 (-.01,.01)	.01 (.00,.02)	.00 (-.01,.01)
Own Detailing	.02 (.01,.04)	.07 (.06,.09)	.02 (.02,.03)	.01 (.01,.02)	-.01 (-.02,-.01)	.00 (-.01,.01)	.00 (-.01,.01)
Competitive Detailing	.00 (.00,.02)	.02 (.02,.03)	.08 (.07,.10)	.00 (-.01,.01)	-.02 (-.03,-.02)	.00 (-.01,.01)	.00 (.00,.01)
Own Prescriptions	.01 (.01,.02)	.01 (.01,.02)	.00 (-.01,.01)	.06 (.05,.08)	-.01 (-.02,.00)	-.01 (-.01,-.02)	.00 (.00,.01)
Competitive Prescriptions	.00 (-.01,.01)	-.01 (-.02,-.01)	-.02 (-.03,-.02)	-.01 (-.02,.00)	.07 (.06,.07)	.01 (-.01,.03)	-.01 (-.01,,00)
Trend	.01 (.00,.02)	.00 (-.01,.01)	.00 (-.01,.01)	-.01 (-.01,-.02)	.01 (-.01,.03)	.05 (.04,.06)	.00 (.00,.01)
Trend squared	.00 (-.01,.01)	.00 (-.01,.01)	.00 (.00,.01)	.00 (.00,.01)	-.01 (-.01,,00)	.00 (.00,.01)	.05 (.04,.06)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 1C.3: Covariance of the Demand Parameters of Pravachol

	Constant	Detailing	Competitive Detailing	Own Prescriptions	Competitive Prescriptions	Trend	Trend squared
Constant	.02 (.02,.04)	.00 (.00,.01)	.01 (.00,.02)	.00 (-.01,.02)	-.01 (-.02,.00)	.00 (-.01,.01)	.01 (.01,.02)
Own Detailing	.00 (.00,.01)	.03 (.02,.05)	.02 (.02,.03)	.01 (.00,.02)	-.02 (-.02,-.01)	.00 (-.02,.00)	.00 (.00,.01)
Competitive Detailing	.01 (.00,.02)	.02 (.02,.03)	.03 (.02,.04)	.02 (.01,.02)	.00 (-.02,.02)	.00 (.00,.01)	.00 (-.01,.00)
Own Prescriptions	.00 (-.01,.02)	.01 (.00,.02)	.02 (.01,.02)	.04 (.03,.04)	.00 (-.02,.01)	.00 (-.01,.00)	.00 (.00,.01)
Competitive Prescriptions	-.01 (-.02,.00)	-.02 (-.02,-.01)	.00 (-.02,.02)	.00 (-.02,.01)	.02 (.02,.03)	.01 (.00,.02)	.00 (.00,.01)
Trend	.00 (-.01,.01)	.00 (-.02,.00)	.00 (.00,.01)	.00 (-.01,.00)	.01 (.00,.02)	.03 (.02,.05)	.00 (-.02,.00)
Trend squared	.01 (.01,.02)	.00 (.00,.01)	.00 (-.01,.00)	.00 (-.00,.01)	.00 (.00,.01)	.00 (-.02,.00)	.04 (.03,.04)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 1C.4: Covariance of the Demand Parameters of Zocor

	Constant	Detailing	Competitive Detailing	Own Prescriptions	Competitive Prescriptions	Trend	Trend squared
Constant	.07 (.06,.07)	.01 (-.01,.02)	.01 (.01,.03)	.02 (.01,.03)	-.01 (-.02,.00)	.02 (.02,.03)	.00 (-.02,.01)
Own Detailing	.01 (-.01,.02)	.05 (.05,.07)	.02 (.02,.04)	.01 (-.01,.02)	-.01 (-.03,.00)	.01 (.00,.01)	.00 (-.01,.01)
Competitive Detailing	.01 (.01,.03)	.02 (.02,.04)	.07 (.06,.09)	.03 (.02,.05)	-.02 (-.03,-.01)	.01 (.00,.01)	-.01 (-.01,.01)
Own Prescriptions	.02 (.01,.03)	.01 (-.01,.02)	.03 (.02,.05)	.06 (.05,.07)	.00 (-.01,.02)	.00 (.00,.01)	.00 (.00,.00)
Competitive Prescriptions	-.01 (-.02,.00)	-.01 (-.03,.00)	-.02 (-.03,-.01)	.00 (-.01,.02)	.05 (.04,.05)	.00 (-.01,.00)	.00 (.00,.02)
Trend	.02 (.02,.03)	.01 (.00,.01)	.01 (.00,.01)	.00 (.00,.01)	.00 (-.01,.00)	.05 (.04,.07)	-.01 (-.01,.01)
Trend squared	.00 (-.02,.01)	.00 (-.01,.01)	-.01 (-.01,.01)	.00 (.00,.00)	.00 (.00,.02)	-.01 (-.01,.01)	.09 (.06,.11)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 1C.5: Results of the Detailing Allocation Equation after the Different Policy Shifts

			Con-stant	Prescription Volume			Responsiveness to Detailing			Competitive Detailing Levels		
Shift size	**Shift Initiator**	**Com-pany**		**Low**	**Mid**	**High**	**Low**	**Mid**	**High**	**Low**	**Mid**	**High**
10%	Lipitor	Crestor	.06	-.17*	-.11*	.28*	-.06	-.03	.09*	-.02	-.01	.03
25%	Lipitor	Crestor	.02	-.02	-.05*	.07*	-.11*	-.03	.14*	-.02	-.16*	.18*
40%	Lipitor	Crestor	.32*	-.02	-.03	.05	-.05	-.02	.07*	.08*	-.10*	.02
10%	Pravachol	Crestor	.15*	-.04	-.02	.06	-.07*	-.05	.12*	-.01	-.05	.07*
25%	Pravachol	Crestor	.06*	-.13*	-.08*	.21*	-.08*	.00	.08*	-.05	-.02	.07
40%	Pravachol	Crestor	-.16*	-.24*	-.09	.33*	-.04	-.02	.06	-.12	-.02	.14*
10%	Pravachol	Lipitor	-.03	-.16*	-.03	.19*	-.13*	.02	.11*	-.06	-.04	.10*
25%	Pravachol	Lipitor	-.03	-.14*	.03	.11	-.10*	-.05	.15*	-.07*	-.04	.11*
40%	Pravachol	Lipitor	-.12*	-.21*	-.03	.24*	-.13*	.02	.11*	-.07	-.07	.14*
10%	Lipitor	Prava-chol	-.11*	-.05	-.01	.06	-.12*	-.05	.17*	-.01	-.02	.03
25%	Lipitor	Prava-chol	-.03	-.07	.01	.06	-.09*	-.03	.12*	.00	-.01	.02
40%	Lipitor	Prava-chol	-.05	-.07	-.02	.08	-.04	-.05	.09	.00	-.03	.03
10%	Lipitor	Zocor	.31*	-.11*	.04	.07	-.05	-.03	.08	-.04	-.03	.07*
25%	Lipitor	Zocor	.19*	-.18*	-.02	.20*	-.07*	-.07*	.14*	-.10*	.09*	.00
40%	Lipitor	Zocor	.21*	-.18*	.06	.12	-.07	.05	.01	-.06	-.04	.10*
10%	Pravachol	Zocor	.24*	-.03	-.04	.07	-.04	-.02	.07*	-.12*	.00	.12*
25%	Pravachol	Zocor	.04	-.11*	-.03	.14*	-.04	-.02	.06	-.05	-.15*	.20*
40%	Pravachol	Zocor	.14*	-.12*	-.03	.15*	-.09	-.09	.19*	-.05*	-.04	.09*

* Zero is outside the 95% confidence interval
Note: The results are estimated using effects coding.

The Detrimental Influence of Providing Positively Biased Information to Doctors in Pharmaceutical Sales Calls

Essay 2*

*This essay is based on a paper in collaboration with Stefan Stremersch.

The Detrimental Influence of Providing Positively Biased Information to Doctors in Pharmaceutical Sales Calls

Abstract

The scholarly literature has heavily debated the responsiveness of doctors to pharmaceutical sales calls. Unfortunately, it has overlooked an important firm decision of great managerial and public policy relevance, namely the information content that is provided in sales calls. This paper examines: (1) how responsive doctors are to information provided across different product attributes; (2) whether firms present a positively biased information set to doctors; (3) whether doctors are more or less responsive to positively biased information in sales calls. We use a hierarchical Bayesian VARX model to estimate the effect of information content (i.e. the drug attributes presented) in sales calls on doctors' responsiveness. We find that: (1) firms do not provide information on the right product attributes at their optimal frequency; (2) sales calls include discussion of positively biased information; (3) discussion of positively biased information lowers sales call responsiveness in the long term. Our results imply that firms need to adjust their messaging to optimize doctors' detailing responsiveness and hence ease public concerns on the discussion of positively biased information with doctors.

Introduction

The scholarly literature has heavily debated the responsiveness of customers to sales calls in various industries and its measurement (Albers et al. 2010; Hanssens et al. 2001). Unfortunately, it has largely overlooked an important firm decision, namely the information content that is provided in sales calls and its effects on customers' sales call responsiveness. This lack of attention to information content in the personal selling literature contrasts sharply with the attention it received in the advertising literature. Studies relating advertising content to advertising responsiveness have been conducted for television advertising (e.g. Anderson and Renault 2006; Chandy et al. 2001; Lodish et al. 1995) and for print and banner advertising (e.g. Bertrand et al. 2010; Hanssens and Weitz 1980; Lohtia et al. 2003; Wedel and Pieters 2000).

This paper examines information content provided in sales calls in the pharmaceutical industry; an industry in which scholars have found a particularly large heterogeneity in sales call effectiveness (see Fischer and Albers 2010; Gönül et al. 2001; Kremer et al. 2008; Manchanda and Chintagunta 2004; Manchanda and Honka 2005; Mizik and Jacobson 2004; Narayanan et al. 2005; Venkataraman and Stremersch 2007). In this industry, representatives of pharmaceutical firms visit medical doctors to promote prescription of their firm's drugs (a practice, typically referred to as pharmaceutical detailing).

This industry presents an ideal context to examine information content in sales calls for several reasons (Stremersch and Van Dyck 2009). Pharmaceutical detailing expenditures are very large ($6.3 billion in 2009 in the U.S. according to IMS Integrated Promotional Services, which does not include sampling costs). In the drug category (i.e. statins) we examine, a handful of firms spend more than $400 million annually on detailing. Pharmaceutical detailing is also very well documented by data suppliers, such as IMS Health, which has reliable data on information content in detailing visits.

Information content in pharmaceutical sales calls and doctors' responsiveness is a primary public policy concern and of high managerial interest. On multiple occasions, people have expressed concerns that the information in pharmaceutical sales calls consists of a positively biased, sometimes even illegal, subset of drug information (Anderson et al. 2009; Meier 2007; Roughead et al. 1998; Tipton et al. 2009). Also firms are grappling with the optimal information content in detailing visits (Weintraub 2007). The industry, under

increasing societal scrutiny, is considering a new sales model that should provide the doctor with exactly the right information more effectively.[14]

In the only initial explorations of detailing content of which we are aware, Ziegler et al. (1995) analyze the accuracy of 106 statements of sales representatives about drugs and find that 12 of those statements are incorrect and cast the promoted drug in a more favorable light. Molloy et al. (2002) asked 5 sales representatives to experimentally provide details of low, medium, or high quality to 135 doctors, who subsequently self-reported the extent of learning from the detail. Steinman et al. (2007) examined market research forms on 116 detailing visits in the context of the promotion of off-label usage of gabapentin, which also includes self-reports of doctors' intentions to prescribe.

This paper investigates information content, i.e. which drug attributes are discussed, from a unique database, obtained from IMS Health – a prime supplier on doctor-level data. The database contains 5,011 details to 600 doctors in the U.S., who collectively wrote 728,829 prescriptions for the top three brands in the statin category, in the period between 2002 and 2005, and estimates doctors' responsiveness from their actual prescription behavior. By our knowledge, this is the first large-scale study that examines the impact of information content in detailing on actual prescription behavior. It aims to answer three specific questions.

First, how responsive are doctors to information across different product attributes? We quantify doctors' responsiveness to information on the following product attributes (1 if the attribute was discussed; 0 if it was not): efficacy, indications, price, side effects, and interactions.[15] Second, do firms present positively biased information in their detailing calls to doctors? We combined our database with scientific information from the FDA, the IMS Midas database that includes price information, and a working paper of Sood and Stremersch (2010) on the drug profile across the attributes we examine. Accordingly, we can determine whether attributes indicating that the drug outperforms the competition (i.e. competitive superiority) and attributes about which positive news (e.g. extension of the number of approved indications) or negative news (e.g. new side effects appearing on the label) is released are discussed and the extent to which they are discussed during sales calls. The variation across drugs in their scientific profile allows us to operationalize competitive superiority of the drug, while the variation across time allows us to operationalize whether there is negative or positive news. In this paper, we refer to a

[14] Pharma 2020: Marketing the Future: Which Path Will You Take? PricewaterhouseCoopers, 2009.

[15] Note that a drug may be characterized by additional attributes, such as mechanism of action, patient profile, safety, formulary status, cost effectiveness, and dosing, among others. However, objective (i.e. scientific) data was not available, very complicated or showed no time-variation on these attributes for the drugs we analyzed. Contact with IMS Health revealed that they assessed our selection of attributes as covering the most important product attributes.

sales call containing positively biased information, as a conversation in which competitively superior attributes or attributes with positive news are more often discussed than non-superior attributes and attributes with negative news, respectively. The third question we pose is whether doctors are more or less responsive to positively biased information in sales calls.

To estimate the effect of information content in sales calls on prescriptions, we develop a hierarchical Bayesian VARX model with latent dependent variables (i.e. prescriptions and detailing). The model corrects for the possible endogenous allocation of sales calls and the information content discussed in such sales calls. The model also allows us to estimate the dynamic effects of every detailing visit. We compute generalized impulse response functions, which enable us to explicitly disentangle the immediate and total effects of detailing. We explain the immediate and total effect of detailing by the information content discussed. We include fixed effects per doctor and brand to correct for salesperson-specific effects. We also estimate another model that allows for heterogeneous effects across different segments of doctors.

We find that the firms in our sample do not provide information on the right product attributes at their optimal frequency to maximize the responsiveness of doctors to sales calls in their prescription behavior. While the most frequently discussed attribute, i.e. drug efficacy, and side effects are discussed too frequently, indications, price, and interactions are discussed not frequently enough. Second, we find that sales calls include discussion of positively biased information. Attributes on which the respective drug is competitively superior or for which there is positive news, are discussed more frequently than non-superior attributes and those with negative news. Third, we find that the inclusion of such positively biased information in sales calls may lower the responsiveness of doctors in their prescription behavior. Firms should discuss more balanced (new) product information.

The paper continues by discussing the research context and data. Then, we discuss the model and results, before we conclude with a discussion of the implications, limitations and future research.

Research Context and Data

Research Context

The largest promotional expense made by pharmaceutical firms for branded prescription drugs is to send sales representatives to doctor practices to convince doctors to prescribe their drugs to patients. This practice is commonly known as detailing and the

length of a visit varies from one minute to one hour, but takes, on average, a few minutes. In the U.S. alone, there are approximately 100,000 sales representatives in the pharmaceutical industry. Sales representatives receive extensive training and presentation materials from their firm to steer what they discuss with the doctor to sustain or increase the doctor's prescriptions of the firm's drug, Another reason of this training is to ensure that the information they provide to doctors falls within the ethical policy set by the firm and is within the law. Pharmaceutical firms have a code of ethics for their sales reps.

In the U.S., the FDA regulates prescription drug marketing including detailing. According to the law, drug marketing must be accurate, balance the risk and benefit information, and is consistent with the FDA approved prescribing information. The promotional materials that sales representatives use should only include information supported by strong evidence from clinical studies. To enforce this law, the FDA has a separate division, called the Division of Drug Marketing, Advertising, and Communications (DDMAC). The DDMAC routinely checks direct-to-consumer advertisements, journal advertising and other promotional materials. However, it is tougher for them to check the content of detailing calls as these take place behind closed doors (Roughead et al. 1998). Thus, it is much harder to collect evidence on systematic violations of the law based on private conversations between the sales rep and the doctor.

Our empirical inquiry is situated in the statin category, between September 2002 and December 2005. Statins (HMG-CoA reductase inhibitors; ATC code C10aa) lower excessive cholesterol levels in the blood, particularly low density lipoprotein (LDL) cholesterol.[16] We study the three main drugs in this category, Lipitor, Pravachol and Zocor. These are the best selling drugs during the data period and make up more than 80% of the unit sales in the statin category and more than 90% of the total dollar sales. In our data, on average, within the set of the top 3 brands, Lipitor has a 65% share of unit prescriptions, Zocor has a share of 21%, and Pravachol has a share of 14%.

In particular, our data set, obtained from IMS Health, includes the monthly detailing efforts directed to and monthly number of total prescriptions written by a panel of 600 doctors, representative of the universe of office-based doctors in the continental U.S. It contains 728,829 prescriptions and 5,011 detailing visits. The doctor panel reports online on the detailing visits they receive, the drug attributes that are discussed and the duration of the visit. IMS Health has created a special website to collect this information and gives

[16] Statins may, to a minor extent, also increase high density lipoprotein (HDL) cholesterol and decrease excessive triglyceride levels. Recent evidence has documented pleiotropic effects of statins beyond LDL reduction (i.e. anti-inflammatory properties) (e.g. Liao and Laufs 2005).

the highest priority to collect accurate and complete data.[17] IMS Health is a prime analytic partner, specifically for the pharmaceutical industry and services many pharmaceutical firms. The prescriptions reported by IMS Health are 'projected' prescriptions; this projection corrects for the non-exhaustive coverage (approximately 70%) of pharmacy outlets through an algorithm that is unknown to the researcher, which yields a different multiplier for each month, doctor, and brand. Hence, our prescription data includes zeros and continuous values of one or greater. An average pharmaceutical sales call in our data lasts 4.11 minutes. Table 2.1 shows the various product attributes and the rate at which they are discussed for our three focal statins. Efficacy is discussed in 74% of the sales calls, while, for example, price is discussed in 16% of the sales calls.

In addition, we have collected data on the strength of various product attributes for the top-3 brands in the category mentioned above, from the FDA, the IMS Midas database, and the working paper of Sood and Stremersch (2010).

Information Content in Sales Calls

Our first research question investigates how responsive doctors are to information across different product attributes. Our data include, for each detailing observation, the product attributes that the sales representative and doctor discussed, as reported by the doctor, after the sales call. We distinguish the following product attributes: efficacy, indications, price, side effects and interactions (see Table 2.1 for a description). In our empirical application, we include dummies indicating the discussion of the specific product attribute in that sales call, which we denote for these five product attributes by: *Information_Efficacy*, *Information_Indications*, *Information_Price*, *Information_Side_Effects* and *Information_Interactions*.

Our second and third research question combine the discussion of various product attributes with the scientific evidence that exists for those attributes. The notion of "positively biased information" is then operationalized by interacting the effect of discussing various product attributes with the scientific evidence for the attributes that are discussed. Regarding the drug's scientific profile, we have collected monthly data on the strength of the product attributes we study (e.g. see Azoulay 2002; Cockburn and Anis 1998). We operationalize drug efficacy as the time-varying mean efficacy of statins,

[17] IMS Health strives for high quality data by using several mechanisms. First, panel members are personally trained before participation and receive retraining if necessary. Second, to stimulate doctors to report complete and accurate information, they also participate in a compensation program, which they only qualify for when the data is reported before the deadline and doctors are contacted over the phone or receive reminder emails to report the data frequently. Third, extensive quality control checks are run from recruiting panel members to data collection and verification to sample design to projection and in instances the doctor is contacted to check his reported information.

measured as the mean reduction in LDL cholesterol across all scientific studies at and prior to a certain time period (from Sood and Stremersch 2010). We have collected the time-varying number of indications, number of side effects, and number of interactions for all statins, from the FDA website. We obtained drug prices from the IMS Midas database. Table 2.2 shows the mean and standard deviation for all product attributes.

From the scientific profile of the drug and the attributes discussed in the sales call, we obtain the attribute-level variables on information content, competitive superiority (from comparing the scientific information on the drug attributes across drugs), negative news and positive news (from comparing the scientific information on the drug attributes over time).

Competitive superiority is measured as the number of attributes discussed in a sales call, on which the drug is competitively superior in that month, according to the scientific evidence we obtained. As we have data on five product attributes, this variable potentially ranges from 0 (the sales call did not include any competitively superior attribute) to 5 (the sales call included all attributes and the drug is superior on all attributes). In our data set, this variable takes a maximum value of 4, as no brand is superior on all product attributes at any moment during our data period. We denote this variable as *Information_Competitive_Superiority*.

Negative news is the number of attributes discussed in a sales call, for which negative information is released in that same month, denoted as *Information_Negative_News*. Positive news is the number of attributes discussed in a sales call, for which positive information is released in that same month, denoted as *Information_Positive_News*. Based on scientific evidence, negative (resp. positive) information can be a decrease (resp. increase) in the efficacy, a decrease (resp. increase) in the number of indications, an increase (resp. decrease) in price, an increase (resp. decrease) in side effects, or an increase (resp. decrease) in the number of interactions. The variables measuring positive and negative news range from 0 to 3 in our data set.

Other Variables

As we are interested in the effect of positively biased information, we need to control for the amount of new information released (i.e. the number of attributes new information is released on), which we will denote as *Information_New*. To obtain this variable, we first standardize the product attributes across brands, then compute the absolute differences in the standardized attribute value for month *t* compared to month *t-1*, after which we sum these absolute differences for the attributes discussed in a sales call for the focal brand. For example, side effects are discussed in a particular sales call and in the

same month the FDA has updated their label with regards to side effects. If two side effects are added to the label, there will be more new information than if only one side effect is added. The *Information_New* variable has mean .02 and ranges from 0 to 1.01 (a sales call for Pravachol, in which efficacy, indications, and price were discussed, in a month with substantial changes for those attributes). We also control for the duration of the sales call in minutes, denoted as *Duration.*

Model

To model the effect of information content in the sales call on detailing responsiveness, we want to estimate the determinants of the dynamic effects of detailing. We posit a model that allows estimating a separate immediate and total effect for every detailing call and subsequently relates these effects to the content of detailing. Thereby we also need to account for the endogeneity of detailing and detailing content, which is discussed in more detail later. A vector autoregressive model with exogenous variables (VARX) is ideally suited to account for endogeneity, by jointly modeling prescriptions and detailing, and is able to capture the dynamic effects of each individual sales call. The model accounts for heterogeneity, by incorporating individual-, brand- and time-specific variables. An extra challenge is that, due to the nature of the data, the model needs to handle latent dependent variables. Recent applications of VAR models in marketing are Luo (2009) and Slotegraaf and Pauwels (2008), among many others.

As our VARX model does not capture the immediate and total effect of detailing on prescriptions directly by separate coefficients, we use impulse response functions to compute this effect over time. Subsequently, we estimate the effect of information content on the immediate and total detailing responsiveness. Ideally, we would perform these steps in an integrated procedure (e.g. Fok et al. 2006). However, given that our model has latent dependent variables, such an integrated procedure is not feasible. While our approach generates unbiased coefficients (given that it satisfies various standard assumptions, such as homoscedastic errors), it loses some estimation efficiency. We compensate for this by our large estimation sample.

Prescription and detailing model: Below we specify our model consisting of $J=3$ brands (Lipitor, Zocor and Pravachol). In our model, doctors are indicated by $i = 1...I$ and time by $t = 1...T$. The prescriptions are a continuous variable, truncated from below at zero, and detailing is a count variable. Therefore, we model the latent values for both, indicated by Rx^{*}_{ijt} and Det^{*}_{ijt}, in a VARX(P) system with P lags.

$$\begin{bmatrix} Rx^*_{i1t} \\ Rx^*_{i2t} \\ Rx^*_{i3t} \\ \ln(Det^*_{i1t}+1) \\ \ln(Det^*_{i2t}+1) \\ \ln(Det^*_{i3t}+1) \end{bmatrix} = \begin{bmatrix} \beta_{i11}+\beta_{i12}Trend_t+\beta_{i13}IntroCrestor_t \\ \beta_{i21}+\beta_{i22}Trend_t+\beta_{i23}IntroCrestor_t \\ \beta_{i31}+\beta_{i32}Trend_t+\beta_{i33}IntroCrestor_t \\ \beta_{i41}+\beta_{i42}\ln(Trend_t)+\beta_{i43}IntroCrestor_t \\ \beta_{i51}+\beta_{i52}\ln(Trend_t)+\beta_{i53}IntroCrestor_t \\ \beta_{i61}+\beta_{i62}\ln(Trend_t)+\beta_{i63}IntroCrestor_t \end{bmatrix} +$$

$$\sum_{p=1}^{P} \begin{bmatrix} \gamma^p_{it11} & \gamma^p_{it12} & \gamma^p_{it13} & \gamma^p_{it14} & \gamma^p_{it15} & \gamma^p_{it16} \\ \gamma^p_{it21} & \gamma^p_{it22} & \gamma^p_{it23} & \gamma^p_{it24} & \gamma^p_{it25} & \gamma^p_{it26} \\ \gamma^p_{it31} & \gamma^p_{it32} & \gamma^p_{it33} & \gamma^p_{it34} & \gamma^p_{it35} & \gamma^p_{it36} \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} Rx_{i1,t-p} \\ Rx_{i2,t-p} \\ Rx_{i3,t-p} \\ Det_{i1,t-p} \\ Det_{i2,t-p} \\ Det_{i3,t-p} \end{bmatrix} +$$

$$\sum_{p=1}^{P} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma^p_{it41} & \gamma^p_{it42} & \gamma^p_{it43} & \gamma^p_{it44} & \gamma^p_{it45} & \gamma^p_{it46} \\ \gamma^p_{it51} & \gamma^p_{it52} & \gamma^p_{it53} & \gamma^p_{it54} & \gamma^p_{it55} & \gamma^p_{it56} \\ \gamma^p_{it61} & \gamma^p_{it62} & \gamma^p_{it63} & \gamma^p_{it64} & \gamma^p_{it65} & \gamma^p_{it66} \end{bmatrix} \begin{bmatrix} \ln(Rx_{i1,t-p}+1) \\ \ln(Rx_{i2,t-p}+1) \\ \ln(Rx_{i3,t-p}+1) \\ \ln(Det_{i1,t-p}+1) \\ \ln(Det_{i2,t-p}+1) \\ \ln(Det_{i3,t-p}+1) \end{bmatrix} + \begin{bmatrix} \varepsilon_{i1t} \\ \varepsilon_{i2t} \\ \varepsilon_{i3t} \\ \varepsilon_{i4t} \\ \varepsilon_{i5t} \\ \varepsilon_{i6t} \end{bmatrix}, \qquad (2.1)$$

with Σ the covariance matrix of the residuals $[\varepsilon_{i1t}, \varepsilon_{i2t}, \varepsilon_{i3t}, \varepsilon_{i4t}, \varepsilon_{i5t}, \varepsilon_{i6t}]'$. The observed number of details Det_{ijt} is Poisson distributed:

$$\Pr(Det_{ijt} = l \mid Det^*_{ijt}) = \left(\frac{\exp\left(-Det^*_{ijt}\right) \cdot \left(Det^*_{ijt}\right)^l}{l!} \right), \qquad \text{for } j = 1 \ldots J, \qquad (2.2)$$

and allows for overdispersion through the covariance matrix Σ (Chib and Winkelmann 2001).

We take the natural logarithm of detailing as the dependent variable to ensure positivity in Equation (2.1) and therefore we need to split the matrix with autoregressive parameters in two parts. Where necessary, we add one to the log-transformed variables to prevent evaluation problems due to zeros (see also Manchanda et al. 2004). The variable *Trend* indicates a linear trend for prescriptions and for the detailing equations, we include a logarithmic trend. As the Poisson model uses a log-link function, the trend will have an approximately linear effect on the number of details. *IntroCrestor* is a dummy taking the value one after the introduction of Crestor to the market in August 2003, and 0 otherwise.

The β-parameters are individual-specific and multivariate normally distributed $\text{vec}(\beta_{il}) = \text{MVN}\left(\text{vec}(\overline{B_l}), \Omega_{Bl}\right)$ for $l = 1 \ldots 2J$, with Ω_{Bl} a full covariance matrix within dependent variable l. The γ_{it} are individual- and time-specific of size $2Jx2J$ with $\text{vec}(\gamma_{it}) = \text{MVN}\left(\text{vec}(\overline{\Gamma}), \Omega_{\Gamma}\right)$, where Ω_{Γ} is a $(2J)^2 x (2J)^2$ diagonal matrix. The estimation steps are discussed in detail in Appendix 2A.

Immediate and total effects of detailing: We calculate the immediate and total effects of detailing using generalized impulse response functions (GIRFs), measuring the time profile of a shock of one additional detail to the system on future values at any given point in time (Pesaran and Shin 1998).

$$GIRF_{ijt}(n, \delta, I_{t-1}) = \text{E}(Y_{ij,t+n} \mid \delta, I_{t-1}) - \text{E}(Y_{ij,t+n} \mid I_{t-1}), \tag{2.3}$$

$$IE_{ijt}(\delta, I_{t-1}) = \text{E}(Y_{ijt} \mid \delta, I_{t-1}) - \text{E}(Y_{ijt} \mid I_{t-1}), \tag{2.4}$$

$$TE_{ijt}(\delta, I_{t-1}) = \sum_{n=0}^{\infty} \text{E}(Y_{ij,t+n} \mid \delta, I_{t-1}) - \text{E}(Y_{ij,t+n} \mid I_{t-1}). \tag{2.5}$$

Here *IE* and *TE* denote the immediate and total effect, respectively, following the terminology used in Fok et al. (2006) and Pauwels et al. (2002). n represents the number of periods over which the effect is measured, δ is the shock given to the system and I_{t-1} is the information set containing all the known variables at time $t-1$. Note that the total effect includes the immediate effect and the objective of firms should always be to optimize the total effect.

We use the GIRF as it is invariant to the ordering of the variables in the model (Pesaran and Shin 1998). To compute the effect of one additional detailing visit we set δ equal to one for the dependent variable we are shocking and the other elements are equal to σ_{ml}/σ_{ll} for $m \neq l$, due to the immediate effects of detailing (Dekimpe and Hanssens 1999). We only compute the effect for the months in which at least one detail took place. Hereby, we take the nonlinearity and truncation of our dependent variables into account. Hence, we consider the effect of an increase in detailing of one unit at time t. Using the draws of the MCMC estimation, we naturally account for all types of uncertainty around the GIRF outcomes (Koop 1992).

Detailing allocation has been found to be based on doctors' prescription volume, the level of competitive detailing and detailing responsiveness (Fugh-Berman and Ahari 2007; Manchanda et al. 2004). This might create an endogeneity problem. Our VARX model treats detailing as an endogenous variable and hence corrects for firms' strategic detailing allocation across doctors. We directly correct for the dynamic effects of strategic

allocation based on prescription volume and competitive detailing by including past prescriptions and competitive details in the detailing equation and a full covariance matrix between own detailing, competitive detailing and prescriptions (Dekimpe and Hanssens 1999). The VARX structure also controls for possible endogenous information content based on observable characteristics, such as prescription behavior and past detailing. This form of endogeneity might arise if firms target information content towards different doctors and this is subsequently more effective. We can not directly control for the endogeneity of detailing responsiveness as its effect can only be obtained by impulse response functions. However, its effect is partly controlled for by the other variables. The part of detailing responsiveness correlated with prescription volume, competitive detailing and the carryover effect of detailing and prescriptions is corrected for by the model. The advantage of our model is that all three measures are time-varying and they correct for possibly changing detailing preferences over the data periods. Nevertheless, we cannot be sure that we fully control for strategic detailing allocation based on detailing responsiveness, which gives the risk of overestimating the responsiveness to detailing. We control for this possible overestimation by taking a doctor-brand fixed effect of detailing responsiveness in the second part of our model, which we discuss below.

In a second step, we estimate the effect of the content of the sales message on the individual-, brand- and time-specific GIRFs. We use a Bayesian weighted linear regression to account for the uncertainty around the GIRFs, which otherwise creates heteroscedastic errors. We weight the dependent and independent variables by one divided by the standard deviation of the individual-, brand- and time-specific GIRF.

$$\begin{aligned}\begin{bmatrix}\Delta IE_{ijt}\\ \Delta TE_{ijt}\end{bmatrix} = {} & \gamma_1 \Delta Information\_Efficacy_{ijt} + \gamma_2 \Delta Information\_Indications_{ijt} + \\ & \gamma_3 \Delta Information\_Price_{ijt} + \gamma_4 \Delta Information\_Side\_Effects_{ijt} + \\ & \gamma_5 \Delta Information\_Interactions_{ijt} + \\ & \gamma_6 \Delta Information\_Competitive\_Superiority_{ijt} + \\ & \gamma_7 \Delta Information\_Negative\_News_{ijt} + \\ & \gamma_8 \Delta Information\_Positive\_News_{ijt} + \gamma_9 \Delta Information\_New_{ijt} + \\ & + \gamma_{10} \Delta Duration_{ijt} + \gamma_{11} \Delta Duration_{ijt}^{\,2} + \xi_{ijt},\end{aligned} \tag{2.6}$$

with $\xi_{ijt} \sim$ MVN$(0,\Xi)$. The independent variables are defined and discussed in the data section before. ΔIE_{ijt} (and ΔTE_{ijt}) are the differences to the individual- and brand-specific mean immediate (and total) effects of detailing and Δ indicates that we take first differences, to allow for fixed effects. We use doctor-brand fixed effects estimation to

correct for all time-invariant characteristics that influence the doctor's responsiveness to detailing for a specific brand. This accounts for various possible forms of endogeneity. First, as mentioned above, the endogenous allocation of detailing based on the doctor's responsiveness might create an upward bias in the size of the detailing effect. As far as this upward bias is present, the doctor-brand fixed effect controls for eliminates it. Second, some sales representatives, because of training or idiosyncratic qualities, may be better in discussing certain types of information than others, and may discuss that more frequently. If this is true, it may lead the model to overestimate the effect of information content on prescriptions. The fixed effects control for the quality of the sales representative, under the assumption that doctors are visited by the same sales representative over time for a specific drug. According to discussions with pharmaceutical managers, this assumption is valid.. Third, the fixed effect captures other time-invariant doctor preferences for information, which might be used by the sales rep to discuss specific information to which the doctor is more responsive. Hence, the estimation of the effect of information content is now based on deviations from the average sales call and delivers unbiased and consistent estimates of the effect of information content on detailing responsiveness.

Results

This section starts by introducing the basic results of our models. Then, we turn to the three research questions we posed at the outset of this paper. This is followed by an extra analysis that examines the heterogeneity in doctors' reactions to positively biased information. We end by presenting the results for the other variables and the robustness tests we conducted.

Basic Results

Before estimating the VARX model of Equation (2.1), we test for unit roots. We use the unit root test for heterogeneous panels of Im et al. (2003). Using time-invariant parameters, the results for the test, including an intercept and no deterministic trend terms, strongly reject the presence of a unit root (P = .002). We select a lag length of 1 as the VARX(1) is already flexible due to the individual-, brand- and time-specific variables. The dynamic effects of detailing on prescriptions and vice versa cannot be easily interpreted from the VARX(1) model as it contains immediate and lagged effects of both, which are partly hidden in the error terms. The estimation results, from Equation (2.1) and (2.2), are given in Appendix 2B (Table 2B.1-2B.5) and are based on 600 doctors over 40 months.

For interpretation of the effects, we extract the immediate and total effect of detailing on prescriptions for every doctor, brand and month. Based on the GIRFs, we can

calculate the average fixed detailing effects across all doctors (Table 2.3). Figure 2.1 shows the average GIRFs. The immediate fixed effects (column 2 in Table 2.3) are the effect of one additional detailing visit on the number of prescriptions for the month in which the detailing visit took place. The total fixed effects (column 3 in Table 2.3) are the cumulative effect of one additional detailing visit on the number of prescriptions over the current month and all the future months. The immediate fixed effects range from .13 for Lipitor to .16 for Pravachol. The total effects are substantially higher for all brands. One detailing visit for Lipitor leads to .44 extra prescriptions in the long term. For Zocor and Pravachol these effects are .29 and .56, respectively. These total effects last at most for 10 months. The total effects are relatively small and are in line with the literature on pharmaceutical marketing (cf. Mizik and Jacobson 2004; Stremersch and Van Dyck 2009). It is important to note though that on each visit, which costs the firm between $120 and $150, a sales rep typically promotes three brands, instead of just one.

Table 2.4 gives the results for the immediate (column 2) and total (column 3) detailing responsiveness. These estimates are based on 3,496 sales calls. The R^2 for immediate detailing responsiveness model is .29 and for the total detailing responsiveness .46.

Doctors' Responsiveness to Information on Product Attributes

Table 2.4 shows the effects of discussing the five product attributes (efficacy, indications, price, side effects and interactions) on detailing responsiveness. The estimates represent the average effect of discussing a certain product attribute across doctors. Discussing drug efficacy in the sales call has a negative impact on the immediate (-.10) and total (-.10) detailing responsiveness. Discussing information about indications or price has a significantly positive effect on both the immediate and total detailing responsiveness, ranging from .06 to .12. Discussing side effects decreases the immediate (-.06) and total (-.05) detailing responsiveness. Discussing interactions has an insignificant immediate effect, but its total effect on detailing responsiveness is positive (.06).

We can contrast the effects of discussing various product attributes with the rate at which they are discussed. Efficacy is the most discussed attribute (see Table 2.1), but has a negative effect on total detailing responsiveness (see Table 2.4). Thus, under the assumption of marginally decreasing effects of discussing product attributes (i.e. the effect of discussing a product attribute on prescriptions decreases the more often it is discussed), sales representatives discuss the efficacy of a drug too often. The opposite is true for price, which is among the least discussed attributes (see Table 2.1) (see also Allan et al. 2007), but has the most positive impact on total detailing responsiveness (see Table 2.4). We

conclude that sales representatives in our data window in this category do not discuss product attributes at their optimal frequency to maximize doctors' responsiveness.

Positively Biased Information in Pharmaceutical Sales Calls

Table 2.5 shows the extent to which sales calls contain positively biased information, i.e. contain information on attributes on which the brand is superior compared to competitors or for which positive (vs. negative) news for the brand is released. Columns 2-4 show the rate at which positive or negative news is discussed in a sales call at the brand level. The last column shows the rate of discussion averaged across brands. Note that the rate of discussion for competitively superior attributes is only defined over brands and not for each brand separately. The percentages for discussing attributes on which there is negative or positive news are conditional on the fact that the type of product information is available (i.e. that that kind of news is released).

If an attribute is superior to its competitors, it is 3 percentage points more likely to be discussed that month than the same non-superior attributes of the competitors are discussed by sales representatives of those competitors.[18] When negative information about a product attribute of Lipitor is released, Pfizer sales reps discuss this attribute in 59% of Lipitor's sales calls that same month, while they discuss positive information in 64% of their sales calls. Across all brands, we observe a similar pattern that when positive information about a drug attribute is released, sales reps detailing such drug discuss it more often than when new negative information is released. Therefore, we conclude that pharmaceutical sales reps provide positively biased information in terms of the attributes they discuss in a sales call.

Effect of Positively Biased Information on Sales Call Responsiveness

Rows 6-8 of Table 2.4 show the effect of information content – as operationalized by discussing competitively superior attributes and attributes on which negative or positive news is released – on detailing responsiveness. The immediate effect of discussing competitively superior attributes on prescriptions is .03, while its total effect is -.06. The sign of this effect changes one month after the sales call to the doctor. Discussing attributes on which negative news is released has a negative immediate effect (-.05), while its total effect is positive (.09). The direction of this effect changes one month after the sales call occurred. Discussing attributes on which positive news is released has an insignificant immediate and total effect. Overall, we can conclude that discussing positively biased

[18] Note that there is quite some variation over time on which drug is superior on an attribute. For example, in our data period, all three drugs score at a certain point best on the mean efficacy across various clinical studies about these drugs that are released over time.

information (competitively superior attributes and more positive than negative new attribute information) in a sales call may lead to positive immediate effects on detailing responsiveness, but in the long run it leads to detrimental effects. As the total effect in our model includes the immediate effect, our findings document suboptimal behavior by pharmaceutical sales representatives.

The contrast between the immediate and total effects may be related to the persuasive and informative effect of sales calls (Hurwitz and Caves 1988; Narayanan et al. 2005). If the persuasive effect prevails, the positive immediate effect for the discussion of competitively superior attributes and the negative immediate effect of discussing negative new product information might, among other things, be explained by the stimulus-response compatibility effect (e.g. Levin et al. 1998). That theory states that the general tone of the message is transferred to the product under discussion. In the longer term, we find that these effects are reversed, very likely because they negatively affect the credibility of and trust in the sales representative (Darke and Ritchie 2007; Doney and Cannon 1997). Etgar and Goodwin (1982) show a parallel to this finding in the advertising literature for new products (our sample contains mature products), as they find that a two-sided advertising message yields a more favorable attitude towards the brand than a one-sided message. They argue that a two-sided message increases the credibility of the message and immunizes customers to future attacks of competitive products.

Heterogeneity in Positively Biased Information

Pharmaceutical firms do not approach all doctors in a similar way. Doctors are generally targeted based on their prescription behavior, detailing responsiveness and competitive detailing (Fugh-Berman and Ahari 2007; Manchanda et al. 2004). Below we explore how the discussion of positively biased information and its effect on detailing responsiveness differs across these three target dimensions.

We divide doctors into different target groups according to three characteristics: (i) their prescription volume, (ii) their responsiveness to detailing, (iii) the number of competitive details they receive. For all three dimensions, we create two groups: the doctors that belong to the top 10% on that dimension and the rest.[19]

Table 2.6 shows how often the various firms discuss negative and positive information across these different groups. First, we observe that the differences between segments are larger for negative than for positive new information. This suggests that sales representatives actively differentiate on whether they discuss negative new product

[19] This split is in line with the decile system of pharmaceutical firms. We split the sample at the top decile as the number of details is heavily skewed towards the doctors that prescribe more, are more responsive and receive more competitive details. In this way, we get groups of relatively equal size.

information with a doctor. Second, the sales representatives for Zocor do not seem to tailor the content based on these segments, while the other two brands target the information based on all three dimensions. Interesting to note is that the targeting strategies of Lipitor and Pravachol are not different from each other.

Table 2.6 also shows the rate of discussion for competitively superior and non-superior drug attributes. The differences across target dimensions are small. Noteworthy is that competitively superior (vs. non-superior) attributes are 7 percentage points more likely to be discussed with doctors that are highly responsive to detailing.

We have also estimated the effects of positively biased information on detailing responsiveness for the various target groups. The results are in Table 2.7. The R^2 of these models is higher than the models without heterogeneity, .35 for the immediate effects and .51 for the total effects. The parameters that are not interacted with the segments are very similar to the results discussed earlier.

The effect of discussing competitively superior attributes, for doctors that are highly responsive to detailing (-.15) and doctors that receive many competitive details (-.11), on total detailing responsiveness is more negative than average. The effect of discussing negative new product information also differs substantially across the segments. The positive effect of discussing negative new information is higher for high-volume prescribers both on the immediate (.09) and the total (.13) detailing responsiveness. Doctors that receive many competitive details also show a higer immediate (.06) and total (.11) effect when new negative product information is discussed. This provides evidence for the argument of Etgar and Goodwin (1982) that it is better for a firm to discuss negative new information by itself rather than a competitor. For positive new information we only observe a significant effect for high prescribers (-.14).

Comparing these results to firm behavior, we observe that only Lipitor sales reps are exploiting this heterogeneity in a somewhat profitable way. The sales representatives of Lipitor discuss negative new information more than average with the target groups for which it has the most positive effect, the high prescribers and the doctors that receive many competitive details.

These results give two main insights. First, there is substantial heterogeneity in the type of doctors with whom positively biased information is discussed and its subsequent effects on detailing responsiveness. Second, we observe that firms deal very differently with this heterogeneity. Lipitor seems to exploit it, Zocor does not do anything with it and Pravachol seems to use it in a counterproductive way.

Other Effects

The determinants of immediate and total detailing responsiveness also include some control variables, shown in Table 2.4. Discussing attributes about which new information is released has an insignificant immediate and total effect. If we combine the linear and quadratic effect of the duration of the sales call, it does not have a significant influence on the immediate and total detailing responsiveness This is in contradiction with Weitz and Bradford (1999). However, we correct for the type and amount of information content of the sales message, which they do not. The result is more in line with the study of Singh and Cole (1993) on the length of television commercials. They find that informational ads of 15 or 30 seconds can have the same effect, while for persuasive ads longer ads are more effective.

Robustness

We have conducted various robustness checks on the functional form of our equations. In Equation (2.6), we have included interaction effects between the information content and the age, gender and geographic location of the doctors. We found little evidence for these interaction effects to be present. We have also estimated the effect of information content in Equation (2.6) per brand. Here, we observed several differences between Lipitor on the one hand and Zocor and Pravachol on the other hand. For example, the total effect of discussing price was positive, but insignificant, for Lipitor, and significantly positive for the other two brands. In our final specification, we have chosen not to include these attribute-brand interactions as it caused some multicollinearity problems for the full equation. Our main results, however, did not change across these models.

We have also tested the robustness for the operationalization of the variables *Information_New*, *Negative_New_Information, Positive_New_Information* and *Competitive_Superiority*. Their effect does not only have to apply in the month that the new information about the drug attributes was released, but can have an effect if it is discussed in the months after. Therefore, we have operationalized all three variables also as moving averages over 2 to 4 months. We find that such operationalizations do not change our main results, they mainly increase the uncertainty around our estimates.

Conclusion, Implications and Limitations

Conclusion

In this study, we investigate the role of information content in personal selling. Information content has been overlooked in the personal selling literature, while the same literature considers the sales message to be the core of the interaction between sales representative and customer (Churchill et al. 2000). In the pharmaceutical industry, the context of this research, large heterogeneity has been found in the effect of personal selling, also referred to as detailing, on prescriptions. We investigate the role of information content in this context, answering the following three research questions.

First, we investigate how the information content that sales representatives discuss with the doctor affects doctors' responsiveness to the sales call. We find that sales reps do not discuss product attributes at their optimal frequency. Sales reps discuss drug efficacy in about 75% of the sales calls, while discussing this attribute has a negative immediate and total effect on detailing responsiveness. They also discuss side effects of the drug too frequently. On the other hand, discussing indications, price and interactions of the drug increase the sales call effectiveness and, hence, sales reps should discuss them more often.

The second and third research question investigate whether firms present a positively biased information set to doctors, and if they do, whether it pays off for firms in terms of larger responsiveness to sales calls. We find that firms are more likely to discuss positive new information about a drug than negative new information. Also, they discuss competitively superior attributes more often than their non-superior counterparts. Our findings show that this strategy is successful in the short term, but not so in the long term. To maximize the return to detailing in the long term, it is more effective to discuss more balanced new product information and more often non-superior product attributes.

Managerial Implications

The findings reported above are highly relevant for managers and public policy administrators. We offer a model for managers to assess the impact of the information content in a detailing call on the detailing responsiveness. In the category we study, statins from 2002 to 2005, we find that firms' detailing was suboptimal in the frequency at which positive information (i.e. attributes on which a drug is competitively superior and on which there is positive news) and specific product attributes (e.g. efficacy and price) are discussed. This finding underlines that monitoring and subsequently optimizing information content in detailing calls is worth the effort.

Firms can optimize information content in detailing calls in several ways. First, firms typically compensate sales reps on the basis of achieving short-term objectives for their own region. Such policy, given the contrast between immediate and total effects in our model, may actually stimulate sales reps to present positively biased information, endangering a trusting relationship between sales rep and doctor, which is in the firm's best interest in the long run (Weitz and Bradford 1999; Wotruba 1991). Therefore, firms should match short-term objectives with long-term objectives in their compensation schemes for sales reps. Some firms are conceiving a change in their sales rep compensation strategy in line with our recommendation – GlaxoSmithKline is an example going public on such plans for 2011[20] – by using doctor feedback, through surveys or personal interviews, for this purpose. Our model shows an alternate or complementary route for such long-term evaluation, namely the estimation of a dynamic model, including information content, on IMS Health data.

Second, how to build trust between sales rep and firm, on the one hand, and doctors, on the other hand, may depend upon the type of doctors. Each pharmaceutical firm has a different way to segment its doctors. Among brand preference, prescription volume, these segmentation criteria may include intrinsic motivations of the physician, e.g. whether the physician is especially triggered by scientific evidence, empathy towards the patient or business considerations. Obviously, from this perspective, doctors may need different information content. Our model allows mapping the effectiveness of information content to different doctor profiles, which would enable firms to customize its information content to the doctor profile (an example for doctor profiling according to volume, responsiveness and competitive detailing, is available from the authors upon simple request).

Third, pharmaceutical firms have been used to detail on the drug's scientific profile (mainly effectiveness and side effects) and not on the drug's price. Doctors typically did not account for price in their prescription choice (Gonul et al. 2001; Gonzalez et al. 2008; IIzuka and Jin 2007). However, pharmaceutical costs are the fastest growing component of healthcare costs in developed countries and especially given the ageing of the population, in recent years increasing attention has been paid by the government to the sustainability of healthcare expenses. Over the last decade, patients have become also more involved in the prescription decision process (McNutt 2004; Alexander et al. 2005). These development has led doctors to focus more and more on the price of the prescription drugs.

[20] GlaxoSmithKline press release, "GlaxoSmithKline to Implement New Compensation Program for U.S. Sales Professionals", July 26, 2010. Accessible at http://us.gsk.com/html/media-news/pressreleases/2010/2010_us_pressrelease_10067.htm.

Our data is from an interesting time period during which this shift in attention took place. Thus, firms will need to shift their detailing model and discuss price and reimbursement considerations with doctors to enhance their responsiveness to detailing.

Fourth, from an ethical viewpoint, the positive bias in information content may damage the degree to which doctors, but also society at large, trust the pharmaceutical industry. The industry should take more measures to safeguard the ethics of its large salesforces and the messaging that they undertake. Even though the pharmaceutical industry has done a lot already in terms of ethics in recent years, more ethics training to sales reps, better monitoring of message content and a stricter code of sales ethics industry-wide may be required to further improve the trust of doctors and society in the industry.

From a public policy viewpoint, our findings are reason for concern. Using a similar methodology as ours, it would be valuable for public policy administrators to assess whether a positive bias in information content also exists in other categories and is still present in more recent years (e.g. 2009-2010). If it is, appropriate action would be to partner with the industry on an improvement program, rather than the FDA's current strategy of unilaterally enforcing more regulation.[21] There are two reasons for this. First, detailing content is harder to monitor than advertising. Second, our model findings show that the interests in a balanced sales call of the regulator are aligned with the long-term interests of the industry.

Limitations and Directions for Future Research

This study contains the following limitations. First, a sales call is an interaction between the firm and the client. This means that the sales representative does not have the power to fully determine the information content of the sales call. However, we do observe consistent differences among firms in the content they discuss with different types of doctors, implying that firms do have the power to influence the sales message content.

Second, our results are limited to the pharmaceutical industry and to the information content we observe in our data. However, it is not unlikely that they can extend to other industries as well. One can find case evidence of myopic selling in other industries, where it may lead to similar detrimental effects. A recent example is the banking industry. The financial crisis has uncovered that sales representatives in this industry were selling financial derivatives without explaining the risks sufficiently to their clients to maximize sales in the short run. Hence, we deem it fruitful for future research to

[21] E.g. the FDA has launched in 2010 the 'Bad Ad' program, which educates doctors on how to recognize misleading information. The goal is to make detailing truthful and balanced and the program encourages doctors to report practices that go against this.

investigate the role of information content in other industries where personal selling plays an important role.

Beyond addressing specific limitations of the present research, there are also many other possible avenues for future research in this area. First, research could establish differences in the effectiveness of information content in sales calls over new and mature products. For example, Narayanan et al. (2005) find that the informative effect prevails in the beginning of a product's life cycle, while the persuasive effect is stronger later on. Hence, it is interesting to investigate how these two effects are related to the sales message content. Second, it would be valuable to look at competitive effects as well, e.g. how does information content counteracts competitive information content and how does information content influence competitive sales. As drugs within a therapeutic category are often strongly competing with each other, drugs try to differentiate from each other. For example, Dong et al. (2009a) find significant competitive detailing effects between most brands and it would be valuable to investigate how the size is driven by the detailing content. Third, future research may examine how the effect of information content interacts with sales person characteristics and the characteristics of the relation between sales person and customer, as these have been shown to be important determinants of the trust in the salesperson (Doney and Cannon 1997; Weitz 1981). This information can be used to instruct and train sales reps at the individual level. Overall, we call for more research that links the responsiveness to a sales message to its information content.

Tables

Table 2.1: Frequency of Information Content in Detailing Calls for All Attributes

Content	Explanation	Rate at which the Attribute Is Discussed
Efficacy	The ability of a drug to produce the desired therapeutic effect.	74%
Indications	The diseases or symptoms for which the drug can be prescribed.	52%
Price	The costs of the treatment, including price reductions.	16%
Side Effects	Problems that may occur when the treatment goes beyond the desired effect, or coincides with the desired therapeutic effect.	22%
Interactions	Interactions between a drug and other substances that prevent the drug from performing as expected.	13%

Table 2.2: Scientific Profile (Mean and Standard Deviation in parentheses) of Lipitor, Zocor and Pravachol, for All Attributes

	Efficacy	Indications	Price	Side Effects	Interactions
Lipitor	31.99 (5.17)	6.98 (1.61)	216.71 (12.44)	145.08 (.27)	15.00 (.00)
Zocor	34.62 (3.01)	19.50 (5.08)	128.58 (5.80)[a]	82.00 (.00)	16.35 (.77)
Pravachol	26.74 (.24)	12.90 (.44)	283.68 (21.27)	88.15 (.36)	18.00 (.00)

Note: Efficacy is measured as the percentage of LDL reduction. Indications measures the number of indications approved. Price is given in dollars per prescription (usually a 90-day prescription). Side Effects is the number of FDA-approved side effects. Interactions denotes the number of interactions of the drug with other substances.
[a]Note that Zocor is the only brand that has a 5mg dosage of its pill on the market. All brands have further dosages of (10, 20, 40 and 80mg). As a smaller dosage is cheaper, this lowers the average price of Zocor.

Table 2.3: Immediate and Total Average Detailing Effects, Based on the GIRF

	Immediate Fixed Effect	Total Fixed Effect
Lipitor	.13	.44
Zocor	.14	.29
Pravachol	.16	.56

Table 2.4: Estimates for the Determinants of Immediate and Total Detailing Responsiveness

	Immediate	Total
Efficacy	-.10	-.10
	(-.15, -.04)	(-.16, -.03)
Indications	.08	.10
	(.05, .10)	(.03, .16)
Price	.06	.12
	(.01, .11)	(.02, .22)
Side Effects	-.06	-.05
	(-.06, -.05)	(-.06, -.03)
Interactions	.02	.06
	(-.03, .07)	(.00, .12)
Competitive Superiority	.03	-.06
	(.02, .05)	(-.07, -.05)
Negative News	-.05	.09
	(-.08, -.03)	(.03, .15)
Positive News	.03	.00
	(-.01, .06)	(-.06, .08)
New Information	.05	.15
	(-.03, .13)	(-.05, .35)
Duration	.01	.01
	(.00, .01)	(.01, .02)
Duration^2	-.00	-.00
	(-.00, -.00)	(-.00, -.00)
R^2	.29	.46
	N=3,496	N=3,496

Note: The 2.5th and 97.5th percentiles are given in parentheses.

Table 2.5: Discussion of Positively Biased Information in Pharmaceutical Sales Calles

	Lipitor	Zocor	Pravachol	All Brands
Competitively Superior Attributes				33%
Competitively Non-superior Attributes				30%
Negative News	59%	58%	50%	57%
Positive News	64%	61%	56%	61%

Table 2.6: Percentage of Calls in which Various Types of Information Content Are Discussed, Split to Different Doctor Types

		Lipitor	Zocor	Pravachol	All
Superior Attributes	All				33%
	High-volume prescribers				33%
	Low-volume prescribers				33%
	High responsiveness				34%
	Low responsiveness				33%
	High competitive details				32%
	Low competitive details				34%
Non-superior Attributes	All				30%
	High-volume prescribers				31%
	Low-volume prescribers				30%
	High responsiveness				26%
	Low responsiveness				33%
	High competitive details				29%
	Low competitive details				32%
Negative	All	59%	58%	50%	57%
	High-volume prescribers	68%	58%	47%	60%
	Low-volume prescribers	57%	58%	52%	57%
	High responsiveness	46%	57%	53%	52%
	Low responsiveness	62%	59%	43%	58%
	High competitive details	66%	59%	54%	61%
	Low competitive details	49%	57%	42%	51%
Positive	All	64%	61%	56%	61%
	High-volume prescribers	67%	61%	58%	63%
	Low-volume prescribers	63%	61%	56%	61%
	High responsiveness	62%	60%	56%	60%
	Low responsiveness	65%	62%	58%	63%
	High competitive details	65%	62%	57%	63%
	Low competitive details	63%	59%	55%	60%

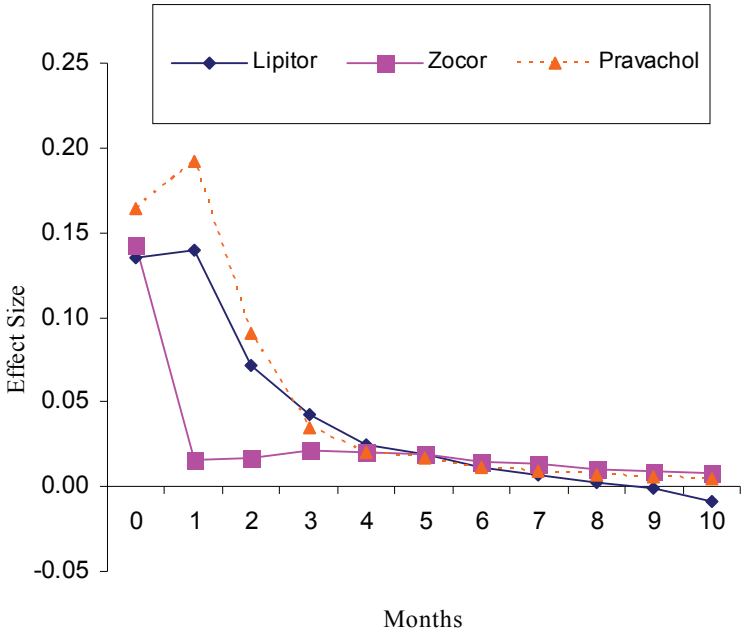
Table 2.7: Estimates for the Heterogeneous Effect of Superiority and Negative New Information on Immediate and Total Detailing Responsiveness

	Immediate	Total
Efficacy	-.12	-.07
	(-.19, -.07)	(-.12, -.01)
Indications	.07	.10
	(.04, .10)	(.01, .19)
Price	.06	.12
	(-.01, .12)	(.02, .23)
Side Effects	-.05	-.04
	(-.06, .05)	(-.05, -.03)
Interactions	.01	.05
	(-.04, .06)	(-.03, .13)
Competitive Superiority	.08	.02
	(.06, .09)	(-.03, .07)
Competitive Superiority High Prescribers	.04	-.02
	(-.03, .09)	(-.11, .07)
Competitive Superiority High Responsiveness	.04	-.15
	(-.00, .08)	(-.26, -.04)
Competitive Superiority High Comp. Detailing	.08	-.11
	(.04, .11)	(-.21, -.03)
Negative News	.09	.05
	(.03, .15)	(-.11, .21)
Negative News High Prescribers	.09	.13
	(.02, .17)	(.03, .24)
Negative News High Responsiveness	.03	.00
	(-.02, .09)	(-.13, .15)
Negative News High Comp. Detailing	.06	.11
	(.00, .11)	(.01, .20)
Positive News	.01	.07
	(-.06, .08)	(-.11, .25)
Positive News High Prescribers	-.07	-.14
	(-.15, .01)	(-.24, -.04)
Positive News High Responsiveness	.04	.03
	(-.02, .10)	(-.04, .11)
Positive News High Comp. Detailing	-.06	.01
	(-.13, -.00)	(-.08, .09)
New Information	.06	.33
	(-.06, .18)	(.02, .64)
Duration	.01	.01
	(.00, .01)	(.01, .02)
Duration^2	.00	.00
	(-.00, -.00)	(-.00, -.00)
R^2	.35	.51
	N=3,496	N=3,496

Note: The 2.5th and 97.5th percentiles are given in parentheses.

Figures

Figure 2.1: Average Generalized Impulse Response Function of Detailing on Prescriptions for Lipitor, Zocor and Pravachol



APPENDIX 2A

This appendix explains the estimation steps of the VARX(P) system for *J* brands and *P* lags. We have taken 220,000 draws and used the first 160,000 for burn-in. In particular, we used a very large thinning value of 300 to store for every draw individual- and time-specific parameter matrices γ. The model is specified as follows:

$$\begin{aligned} Y_{ijt}^{Tr*} &= \sum_{p=1}^{P} \gamma_{ijt} Y_{i,t-p} + \beta_{ij} X_{ijt}^{Tr} + \varepsilon_{ijt}, \qquad \text{for } j = 1 \ldots J \\ Y_{ijt}^{Po*} &= \sum_{p=1}^{P} \gamma_{ijt} \ln(Y_{i,t-p} + 1) + \beta_{ij} X_{ijt}^{Po} + \varepsilon_{ijt}, \qquad \text{for } j = J+1 \ldots 2J. \end{aligned} \tag{2A.1}$$

With $Y_{it} = \left\{ Y_{i1t}^{Tr}, \ldots, Y_{iJt}^{Tr}, Y_{i,J+1,t}^{Po}, \ldots, Y_{i,2\cdot J,t}^{Po} \right\}'$ a vector split up into the truncated variables and the Poisson variables. The Poisson dependent variables are distributed:

$$\Pr(Y_{ijt}^{Po} = l \mid Y_{ijt}^{Po*}) = \left(\frac{\exp\left(- Y_{ijt}^{Po*}\right) \cdot \left(Y_{ijt}^{Po*}\right)^{l}}{l!} \right). \tag{2A.2}$$

The other parameters are distributed as follows: $\varepsilon_{it} = \{\varepsilon_{ijt}, j = 1 \ldots J\} \sim \text{MVN}(0, \Sigma)$, $\text{vec}(\gamma_{it}) = \text{MVN}(vec(\overline{\Gamma}), \Omega_{\Gamma})$, $vec(\beta_{ij}) = \text{MVN}(\text{vec}(\overline{B_j}), \Omega_{Bj})$, for $\forall j$.

We make use of flat priors for all parameters: $\Sigma_{\xi,prior} \sim \text{IW}(r_0, R_0)$, $\text{vec}(\overline{B})_{prior} \sim \text{N}(\text{B}_0, \Omega_{B0})$, $\Omega_{B,prior} \sim \text{IW}(r_{B0}, R_{B0})$, $\text{vec}(\overline{\Gamma})_{prior} \sim \text{N}(\Gamma_0, \Omega_{\Gamma 0})$, $\Omega_{\Gamma,prior} \sim \text{IW}(r_{\Gamma 0}, R_{\Gamma 0})$, with known hyperparameters r_0, R_0, B_0, Ω_{B0}, r_{B0}, R_{B0}, Γ_0, $\Omega_{\Gamma 0}$, $\text{r}_{\Gamma 0}$, $\text{R}_{\Gamma 0}$, and IW$(\cdot,\cdot)$ an Inverted Wishart distribution with *r* degrees of freedom and scale matrix *R*.

The parameters are now drawn by the following sampling scheme:

Step 1: Generate ε_{it}^{Po}. Using Metropolis-Hastings, the candidate is evaluated by the posterior probability:

$$\varepsilon_{it}^{Po} \mid \gamma_{it}, \beta_i, \Sigma \propto \sum_{j=J+1}^{2J} \left(- \lambda_{ijt} + Y_{ijt} \ln(\lambda_{ijt}) \right) - 0.5 \varepsilon_{it}^{Po} \Sigma_{Po,Po}^{-1} \varepsilon_{it}^{Po}, \tag{2A.3}$$

with subscript $Po = J+1 \ldots 2J$ and

$$\lambda_{it}^{Po} = \exp\left(\sum_{p=1}^{P} \gamma_{it}^{Po} Y_{i,t-p} + \beta_i^{Po} X_{it}^{Po} + \varepsilon_{it}^{Po}\right). \tag{2A.4}$$

Step 2: Generate Y_{ijt}^{Tr*}. If $Y_{ijt,trunc} = 0$, the latent Y_{ijt}^{Tr*} is drawn, using data augmentation, from a truncated normal distribution:

$$Y_{ijt}^{Tr*} \mid \gamma_{ijt}, \beta_{ij}, \Sigma \sim \mathrm{TN}(\mu_{ijt}^{*}, \Sigma_{jj}^{*}), \tag{2A.5}$$

$$\mu_{ijt}^{*} = \sum_{p=1}^{P} \gamma_{ijt} Y_{i,t-p} + \beta_{ij} X_{ijt}^{Tr} + \Sigma_{-j,j}^{'} \Sigma_{-j,-j}^{-1} \varepsilon_{i,-j,t}, \tag{2A.6}$$

$$\Sigma_{jj}^{*} = \Sigma_{jj} - \Sigma_{-j,j}^{'} \Sigma_{-j,-j}^{-1} \Sigma_{-j,j}, \tag{2A.7}$$

for $\forall j \in J+1 \ldots 2J$ and *-j* refers to all brands except brand *j*.

Step 3: Generate Γ_{it}. These are drawn using the Metropolis-Hasting algorithm:

$$\gamma_{it} \mid Y_{it}^{*}, \beta_i, \Sigma, \mathrm{vec}(\bar{\Gamma}), \Omega_{\Gamma} \propto -0.5 \varepsilon_{it}' \Sigma^{-1} \varepsilon_{it} - 0.5 \left(\gamma_{it} - \mathrm{vec}(\bar{\Gamma})\right)' \Omega_{\Gamma}^{-1} \left(\gamma_{it} - \mathrm{vec}(\bar{\Gamma})\right), \tag{2A.8}$$

with

$$\varepsilon_{it} = Y_{it}^{*} - \sum_{p=1}^{P} \gamma_{it} Y_{i,t-p} - \sum_{p=1}^{P} \gamma_{it} \ln(Y_{i,t-p}) - \beta_i X_{it}^{Tr} - \beta_i X_{it}^{Po}. \tag{2A.9}$$

Step 4: Generate $vec(\bar{\Gamma})$ and Ω_{Γ}. Using the Gibbs algorithm, these are drawn from a multivariate normal distribution.

$$\begin{aligned} \mathrm{vec}(\bar{\Gamma}) \Big| \gamma_{ijt}, \Omega_{\Gamma} \sim \mathrm{N}\Big(&\Big(\sum_{i,t} z_{it}' z_{it} + \Omega_{\Gamma 0}\Big)^{-1} \\ &\Big(\sum_{i,t} z_{it} \gamma_{ijt} + \Omega_{\Gamma 0} \Gamma_0\Big), \Omega_{\Gamma} \otimes \Big(\sum_{i,t} z_{it}' z_{it} + \Omega_{\Gamma 0}\Big)^{-1}\Big), \end{aligned} \tag{2A.10}$$

with *z* a vector of ones and

$$\Omega_{\Gamma} \big| \gamma_{ijt}, \mathrm{vec}(\bar{\Gamma}) \sim \mathrm{IW}(r_{\Gamma 0} + N(T-P), R_{\Gamma 0} + S_{\Gamma,j}), \tag{2A.11}$$

$$S_{\Gamma,j} = \sum_{i,t} \left(\gamma_{ijt} - \text{vec}(\overline{\Gamma})\right)' \left(\gamma_{ijt} - \text{vec}(\overline{\Gamma})\right) + \left(\text{vec}(\overline{\Gamma}) - \Gamma_0\right)' \Omega_{\Gamma 0} \left(\text{vec}(\overline{\Gamma}) - \Gamma_0\right). \tag{2A.12}$$

Step 5: Generate β_i. These are drawn with a Metropolis Hasting step.

$$\beta_i \mid Y_{it}^*, \gamma_{it}, \Sigma, \text{vec}(\overline{B}), \Omega_B \propto \sum_t -0.5\varepsilon_{it}' \Sigma^{-1} \varepsilon_{it} - 0.5\left(\beta_i - \text{vec}(\overline{B})\right)' \Omega_B^{-1} \left(\beta_i - \text{vec}(\overline{B})\right), \tag{2A.13}$$

with

$$\varepsilon_{it} = Y_{it}^* - \sum_{p=1}^{P} \gamma_{it} Y_{i,t-p} - \sum_{p=1}^{P} \gamma_{it} \ln(Y_{i,t-p}) - \beta_i X_{it}^{Tr} - \beta_i X_{it}^{Po}. \tag{2A.14}$$

Step 6: Generate $\text{vec}(\overline{B})$ and Ω_B.

$$\text{vec}(\overline{B}) \Big| \beta_{ij} \sim \text{MVN} \begin{pmatrix} (\sum_i z_i' z_i + \Omega_{B0})^{-1} (z_i \beta_{ij} + \Omega_{B0} B_0), \\ \Omega_B \otimes (\sum_i z_i' z_i + \Omega_{B0})^{-1} \end{pmatrix}, \tag{2A.15}$$

with z a vector of ones and

$$\Omega_B \mid \text{vec}(\overline{B}), \beta_{ij} \sim \text{IW}(r_{B0} + N, R_{B0} + S_{B,j}), \tag{2A.16}$$

$$S_{B,j} = \sum_i \left(\beta_{ij} - \text{vec}(\overline{B})\right)' \left(\beta_{ij} - \text{vec}(\overline{B})\right) + \left(\text{vec}(\overline{B}) - B_0\right)' \Omega_{B0} \left(\text{vec}(\overline{B}) - B_0\right). \tag{2A.17}$$

Step 7: Generate Σ. This is drawn from an inverted Wishart distribution.

$$\Sigma \mid \gamma_{ijt}, \beta_{ij}, \varepsilon_{ijt} \sim \text{IW}(r_0 + N \cdot (T - P), R_0 + \sum_{i,t} \varepsilon_{it}' \varepsilon_{it}). \tag{2A.18}$$

Appendix 2B

The results from the hierarchical Bayesian VARX(1) system, with latent dependent variables, in Equation (2.1) and (2.2), based on 600 doctors over 40 months, are given below. The estimates for the covariance matrix Σ are given in Table 2B.1. The diagonal elements reflect the size of the dependent variables, where prescriptions have a higher variance than details. Table 2B.2 shows the estimates for the time-invariant coefficients. The constants for prescriptions range from -.38 to 7.29, roughly reflecting the market shares for the different brands. The trend in prescriptions for Lipitor is significantly positive, while the prescription trend for Zocor and Pravachol is negative. This can be explained by the stage of the drugs in the life cycle; while Zocor and Pravachol are nearing their patent expiry in 2006, Lipitor's patent only expires in 2011. The trend in detailing is negative for all brands. The introduction of Crestor has a significant negative effect on the number of prescriptions of Lipitor (-.38) and Zocor (-.23), while it is positive for Pravachol (.10). Its effect on detailing is negative for all brands. Table 2B.3 provides the covariances of these variables per dependent variable and shows that there is large heterogeneity in the population.

Table 2B.4 shows the average own-carryover effects and cross-carryover effects. The carryover effects for prescriptions are in line with the literature and range from .45 for Lipitor to .65 for Pravachol. The effect from lagged detailing on prescriptions is positive for all brands, but smallest for Zocor (.02). We also find positive effects of lagged competitive detailing. Finally, Table 2B.5 describes the heterogeneity in the population of these effects.

Table 2B.1: Covariance Matrix for the Prescription and Detailing Equation

Covariance						
	Rx Lipitor	Rx Zocor	Rx Pravachol	Det Lipitor	Det Zocor	Det Pravachol
Rx Lipitor	3.10	.23	.34	.06	.08	.12
	(2.93, 3.27)	(.10, .32)	(.24, .47)	(.00, .16)	(-.01, .16)	(.05, .25)
Rx Zocor		3.00	.27	.00	.16	.11
		(2.93, 3.09)	(.21, .34)	(-.13, .10)	(.12 .20)	(.07, .18)
Rx Pravachol			2.69	-.06	09	.24
			(2.55, 2.81)	(-.11, .03)	(.02, .17)	(.13, .35)
Det Lipitor				.17	.01	.01
				(.15, .19)	(-.00, .03)	(-.01, .04)
Det Zocor					.16	.03
					(.14, .19)	(.02, .06)
Det Pravachol						.23
						(.17, .32)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 2B.2: Estimates of the Time-Invariant Parameters

Time-Invariant Variables			
	Constant	Trend	Intro Crestor
Rx Lipitor	7.29	2.98	-.38
	(5.48, 9.59)	(1.58, 3.54)	(-.78, -.11)
Rx Zocor	.84	-.83	-.23
	(.39, 1.35)	(-1.65, -.25)	(-.38, -.07)
Rx Pravachol	-1.46	-.81	.10
	(-1.71, -1.21)	(-1.26, -.60)	(.03, .21)
	Constant	Ln(Trend)	Intro Crestor
Det Lipitor	-3.60	-.90	-.64
	(-3.77, -3.47)	(-.97, -.83)	(-.68, -.58)
Det Zocor	-3.73	-.88	-.61
	(-3.78, -3.65)	(-1.00, -.79)	(-.68, -.56)
Det Pravachol	-3.84	-1.13	-.87
	(-3.91, -3.73)	(-1.24, -1.01)	(-.98, -.78)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 2B.3: Estimates for the Population Variance of the Time-Invariant Parameters

Covariance Lipitor Prescriptions			
	Constant	Trend	Intro Crestor
Constant	657.13	-219.29	-91.63
	(605.78, 716.28)	(-241.24, -192.97)	(-104.12, -78.96)
Trend		344.46	21.13
		(312.09, 373.96)	(13.23, 29.67)
Intro Crestor			47.36
			(46.33, 54.96)
Covariance Zocor Prescriptions			
	Constant	Trend	Intro Crestor
Constant	86.52	-49.45	-6.35
	(82.81, 97.89)	(-54.53, -45.28)	(-8.34, -4.53)
Trend		74.16	2.00
		(69.22, 77.31)	(.89, 4.43)
Intro Crestor			7.54
			(6.63, 8.09)
Covariance Pravachol Prescriptions			
	Constant	Trend	Intro Crestor
Constant	25.63	-17.85	-.73
	(23.42, 27.75)	(-20.82, -15.21)	(-1.37, -.33)
Trend		34.72	-2.74
		(29.88, 37.81)	(-3.39, -2.08)
Intro Crestor			2.79
			(2.48, 3.26)
Covariance Lipitor Detailing			
	Constant	Ln(Trend)	Intro Crestor
Constant	2.81	.02	.57
	(2.53, 3.27)	(-.05, .14)	(.52, .67)
Ln(Trend)		1.09	.02
		(.99, 1.17)	(-.08, .09)
Intro Crestor			.65
			(.55, .74)
Covariance Zocor Detailing			
	Constant	Ln(Trend)	Intro Crestor
Constant	2.85	-.30	.62
	(2.53, 3.11)	(-.424, -.0348)	(.55, .72)
Ln(Trend)		1.95	.09
		(1.72, 2.23)	(-.01, .23)
Intro Crestor			.50
			(.46, .60)
Covariance Pravachol Detailing			
	Constant	Ln(Trend)	Intro Crestor
Constant	1.75	-.10	.74
	(1.51, 1.86)	(-.25, .01)	(.65, .83)
Ln(Trend)		.93	-.48
		(.82, 1.06)	(-.53, -.39)
Intro Crestor			.66
			(.61, .73)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 2B.4: Estimates of the Time-Varying Carry-Over Effects

Carry-Over Variables						
	Lagged Rx Lipitor	Lagged Rx Zocor	Lagged Rx Pravachol	Lagged Det Lipitor	Lagged Det Zocor	Lagged Det Pravachol
Rx Lipitor	.45	.11	.03	.20	-.02	.03
	(.44, .45)	(.10, .11)	(.03, .03)	(.19, .21)	(-.03, -.01)	(.02, .05)
Rx Zocor	.01	.48	.07	.04	.02	-.03
	(.01, .02)	(.47, .48)	(.07, .07)	(.04, .05)	(.01, .03)	(-.04, -.03)
Rx Pravachol	.01	.05	.65	.06	.04	.13
	(.01, .01)	(.05, .05)	(.65, .66)	(.04, .07)	(.03, .05)	(.12, .14)
	Lagged Rx Lipitor	Lagged Rx Zocor	Lagged Rx Pravachol	Lagged Det Lipitor	Lagged Det Zocor	Lagged Det Pravachol
Det Lipitor	-.01	-.02	-.03	.03	.02	.01
	(-.01, -.01)	(-.02, -.01)	(-.03, -.03)	(.03, .04)	(.02, .03)	(-.00, .02)
Det Zocor	-.01	-.01	-.01	.11	.02	.05
	(-.01, -.01)	(-.01, -.01)	(-.01, -.01)	(.10, .11)	(.02, .02)	(.05, .06)
Det Pravachol	-.01	-.02	-.02	.16	.09	.03
	(-.01, -.01)	(-.02, -.02)	(-.02, -.02)	(.15, .17)	(.09, .10)	(.03, .04)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Table 2B.5: Estimates for the Population Variance of the Carry-Over Effects

Variance Carry-Over Variables						
	Lagged Rx Lipitor	Lagged Rx Zocor	Lagged Rx Pravachol	Lagged Det Lipitor	Lagged Det Zocor	Lagged Det Pravachol
Rx Lipitor	.12	.01	.01	.22	.32	.21
	(.11, .12)	(.01, .02)	(.01, .01)	(.21, .22)	(.30, .34)	(.20, .23)
Rx Zocor	.00	.07	.00	.18	.17	.18
	(.00, .00)	(.07, .08)	(.00, .00)	(.18, .19)	(.16, .17)	(.17, .19)
Rx Pravachol	.00	.00	.07	.24	.14	.25
	(.00, .00)	(.00, .00)	(.07, .08)	(.23, .25)	(.13, .14)	(.24, .26)
	Lagged Rx Lipitor	Lagged Rx Zocor	Lagged Rx Pravachol	Lagged Det Lipitor	Lagged Det Zocor	Lagged Det Pravachol
Det Lipitor	.00	.00	.00	.03	.07	.10
	(.00, .00)	(.00, .00)	(.00, .00)	(.03, .03)	(.06, .07)	(.09, .10)
Det Zocor	.00	.00	.00	.05	.05	.12
	(.00, .00)	(.00, .00)	(.00, .00)	(.04, .05)	(.05, .05)	(.11, .13)
Det Pravachol	.00	.00	.00	.11	.06	.09
	(.00, .00)	(.00, .00)	(.00, .00)	(.11, .12)	(.06, .07)	(.08, .09)

Note: The 2.5^{th} and 97.5^{th} percentiles are given in parentheses.

Sales Success in Science-Based Industries: Uncovering the Role of Scientific Reviews on Sales and Marketing Expenditures to Users and Experts

Essay 3*

*This essay is based on a paper in collaboration with Ashish Sood and Stefan Stremersch.

Sales Success in Science-Based Industries: Uncovering the Role of Scientific Reviews on Sales and Marketing Expenditures to Users and Experts

Abstract

Firms in science-based industries support the sales of their products with both scientific reviews and marketing expenditures to users or experts. We discern three summary metrics to characterize the body of scientific reviews – valence, dispersion and volume. We differentiate scientific reviews from user and expert reviews and show theoretically and empirically how the summary metrics of scientific reviews impact the marketing expenditures and sales for products in science-based industries. Using a comprehensive dataset of prescription drugs (cholesterol-lowering statins), we show that higher valence increases marketing to both users and experts, while higher dispersion leads to a reallocation of marketing. Higher volume only affects marketing to experts. Product sales are positively affected by both valence and volume. We show that omitting scientific reviews leads to an upward bias in the estimates of marketing responsiveness parameters. Our findings allow firms to anticipate and counteract marketing strategies of competitors given the results of a scientific review of a competitive product. Our method also allows firms to assess the return on investments in scientific reviews.

Introduction

Science-based industries (e.g. biosciences, chemicals, medical electronics, nanotechnology, pharmaceuticals and semiconductors) comprise a substantial part of the economy and are very important for economic growth (Grupp 1996; Mansfield 1991; Narin 2000; Narin, Hamilton and Olivastro 1997)[22]. Firms in science-based industries have higher R&D-to-sales ratios, rely on R&D from both in-house and independent sources (e.g. universities), and outperform their counterparts with a weaker science base (Deng, Lev and Narin 1999; Zucker, Darby and Brewer 1998). Products in science-based industries have a higher number of science papers cited in their patents (science linkage) as compared to products in other industries (Narin 2000; Pavitt 1984). Such products are usually tested in scientific reviews that appear prior to and during the lifecycle of a product. Scientific reviews are product reviews prepared by trained experts through systematic observation, measurement, and experimentation of a product using the scientific method.

Scientific reviews differ from both user and expert reviews on two important dimensions – target audience and level of subjectivity. First, scientific reviews often contain more complex and technical content, which requires more expertise to understand them than expert or user reviews. Thus, scientific reviews are meant for a primarily expert audience in contrast to both user and expert reviews, which target potential users. User reviews are generated by consumers after the consumption of a product and detail their personal experiences for the benefit of other users (Chevalier and Mayzlin 2006). Expert reviews[23] originate from a smaller group of influential people that regularly monitor new or modified products and publicize reviews that have the potential to influence a large number of users (e.g. Mossberg in the *Wall Street Journal*, David Pogue in the *New York Times*, or Oprah Winfrey in her talk show) (Liu 2006; Tellis and Johnson 2007).

Second, scientific reviews are based on tests that use standardized protocols, under controlled conditions, to create scientifically valid results. On the other hand, user and expert reviews do not necessarily adhere to formal scientific testing procedures and are based on consumer product usage experience. As a result, scientific reviews are more

[22] See for detailed information on the role of science in the following science-based industries: biotechnology (Pisano 2006; Zucker, Darby and Armstrong 2002), nanotechnology (Darby and Zucker 2003), pharmaceuticals (Stremersch and Van Dyck 2009), semiconductors (Holbrook et al. 2000).

[23] Alternative names used to refer to expert reviews are critic, professional and third-party reviews.

objective (i.e. based on well-established industry standards), whereas user and expert reviews are, at least partially, subjective[24].

While there is an emerging literature in marketing on the evolution and impact of user and expert reviews on product sales (e.g. Chen and Xie 2008; Zhu and Zhang 2010), relatively little is known about either the impact of scientific reviews on sales or how firms use the outcome of scientific reviews to adjust marketing expenditures. We fill this gap by theoretically and empirically analyzing the interplay between scientific reviews, sales and marketing in science-based industries. Inspired by the prior literature on user and expert reviews, we use three metrics to summarize the available body of scientific reviews – valence, dispersion and volume (e.g. Chintagunta, Gopinath and Venkataraman 2010; Moe and Trusov 2011; Zhu and Zhang 2010). Valence of reviews refers to the average outcome across all available reviews. Dispersion of reviews refers to the variance across all available reviews. Volume of reviews refers to the total number of reviews available.

Prior research suggests that user and expert reviews have the potential to affect sales (e.g. Dellarocas, Zhang and Awad 2007; Liu 2006; Moe and Trusov 2011) and marketing (Chen and Xie 2008). In a theoretical study, Chen and Xie (2008) argue that reviews help consumers identify the products that best match their idiosyncratic preferences and, hence, act as an element of the marketing communication mix. In science-based industries, new scientific reviews appear over the product's lifecycle and provide heterogeneous outcomes on the same product. A reason for this heterogeneity may be that the reviews originate from different sources, manufacturer, independent researchers and competitors, choosing different study designs. Also, manufacturers may sponsor or design new studies intended to showcase higher performance of their products as compared to products of its competitors, e.g. by testing the product in a benevolent environment.

While, scientific reviews may influence sales directly (see Azoulay 2002), firms may also adjust their marketing mix based on the available information (Ippolito and Mathios 1990). Due to the nature of the products, firms in science-based industries often make two types of marketing expenditures – directed to users and to experts. For example, pharmaceutical firms, such as Pfizer, often allocate their marketing budgets for a product across marketing to users (e.g. TV advertising) and experts (e.g. personal selling to physicians). Similarly, DSM, a life sciences and materials sciences-based company, advertises its nutritional ingredients directly to food supplement companies and to end consumers, but also publishes scientific reviews on their products to convince both experts (e.g. dietary supplement companies) and users of the quality of their products. Often this

[24] We acknowledge the existence of scientific misconduct in a small percentage of scientific reviews, where results are falsely reported (New York Times 2006).

demarcation between target audiences is more significant in cases where the decision maker differs from the consumer of the product either because of usage (e.g. B2B manufacturer of a science based product vs. consumer) or competence (e.g. physician vs. patient)

This study answers the following research questions. How do scientific reviews affect a firm's marketing expenditures to users and experts? To what extent do scientific reviews affect sales? To achieve this, we collect a comprehensive body of scientific reviews for an important category of science-based products, namely statins (which are cholesterol-lowering drugs), in the pharmaceutical industry, a prototypical example of a science-based industry (Narin 2000; Stremersch and Van Dyck 2009). We collect all scientific reviews published in top journals by manufacturers, competitors and independent researchers, both prior to and after FDA approval and summarize the body of scientific reviews using three metrics - valence, dispersion and volume. Next, we model the impact of valence, dispersion and volume of scientific reviews on sales, marketing to users (patients) and to experts (physicians) by a vector error correction (VEC) model.

This study has the following contributions: we are the first to comprehensively analyze the role of scientific reviews on sales and on marketing expenditures in science-based industries. We differentiate the impact of scientific reviews on marketing to users from the impact on marketing to experts. We also extend prior literature on user and expert reviews and show how current metrics of valence, dispersion and volume of scientific reviews may be used to investigate a product's marketing expenditures and its sales.

We have the following key findings: A higher valence of the body of scientific reviews increases marketing to both users and experts, while a higher dispersion of the body of scientific reviews leads to a reallocation of marketing expenditures directed towards users to marketing expenditures directed towards experts. A larger volume of the body of scientific reviews has no effect on marketing expenditures directed towards users, but increases marketing expenditures directed towards experts. A higher valence and larger volume of the body of scientific reviews leads to an increase in sales, while the dispersion of the body of scientific reviews has no direct effect on sales. Furthermore, we find that excluding these dimensions of the body of scientific reviews from a sales response model leads to an overestimation of the responsiveness of sales to marketing expenditures.

Our findings allow firms to anticipate what competitors may do given the results of a scientific review and to counteract their marketing efforts to their own advantage. Thus, we provide insights for product managers in pharmaceutical firms to understand and react to marketing strategies of competitors. Second, our method and study provides insights on the value of a scientific review on sales. Firms can use this to assess the return

on investments in scientific reviews. Third, we develop and propose metrics on how to analyze marketing strategy towards users and experts under conditions of changing product performance of both the focal product and competitor products. This distinction is especially relevant for science-based industries, due to the nature of the product and complex nature of scientific reviews. We show how managers can monitor cumulative scientific evidence on a scientific product from multiple sources to evaluate the differential effects of volume, valence, and dispersion on sales and modify the marketing expenditures.

We proceed by discussing the theory on scientific reviews and create hypotheses on their effect on sales and marketing. Then, we present the context, followed by the model and results. We end by discussing the implications of our results.

Theory and Hypotheses

Scientific reviews are an essential component marketers should consider in setting marketing expenditures and may have a substantial effect on sales. There are two main ways of how scientific reviews affect the marketing expenditures of the underlying product. First, scientific reviews may affect the confidence of a firm to change marketing expenditures. Positive scientific reviews increase the confidence managers have in the quality of their products and help them to justify allocation of higher marketing budgets.

Second, scientific reviews affect the amount of information that the firm can provide in its marketing communications. The technical content of scientific reviews requires higher substantive expertise for comprehension of the content and its implications. Therefore, firms may distinguish between general users and experts as two separate target markets. In addition, when many scientific reviews are released over time or when customers do not have the time to read these scientific reviews, firms may need to put in efforts to convey, clarify or stress the new findings to users or experts. They can do that by providing the customers with a verbal discussion of the content, by summarizing the findings or by just facilitating access to the scientific reviews. The firm may also strategically choose what type of information they emphasize.

There are also two main ways of how scientific reviews affect the sales of the underlying product. First, scientific reviews affect sales by changing consumer perceptions about the quality of scientific products. Products in science-based industries are often experience goods (e.g. gecko tape, a nanotechnology-based tape with directional adhesion) or credence goods (e.g. genetically modified vitamin supplements). Assessing the quality of these types of products before purchase involves high costs. In addition, customers engage in more rational decision making during the purchase decision for such products,

which creates a higher demand for high quality, objective evaluation of the product (Dranove and Jin 2010). Scientific reviews provide such information on the performance of the product to consumers.

Second, scientific reviews affect sales by changing the overall uncertainty about the performance of a product in different usage conditions. Firms in the science-based industries place much greater emphasis on the development of new capabilities and the use of intellectual property. Firms face greater competition with respect to the rate at which new products are being introduced and being customized. As a result, there is increased threat of faster obsolescence, changing consumer requirements and uncertain consumer demand, (Pavitt 1984; Narin 2000). Scientific reviews help to address concerns related to consumer education. At the same time, ambiguous or contradicting information might withhold consumers from buying a product.

Building on the arguments given above, we develop six hypotheses on the influence of the valence, dispersion and volume of scientific reviews on marketing expenditures and sales.

Impact of Valence of Scientific Reviews on Marketing Expenditures and Sales

Valence of reviews refers to the average outcome across all available reviews (Basuroy, Chatterjee and Ravid 2003; Chintagunta, Gopinath and Venkataraman 2009; Dellarocas, Awad and Zhang 2004). The valence of the review may be influenced by the chosen design, for which different sources have different incentives. Often a manufacturer attempts to initially identify the best usage conditions for a product and simulate laboratory conditions to test the performance under such conditions. Over time, manufacturers or independent researchers may focus their attention on testing the product under different conditions that may yield different levels of performance, leading to a change in the valence of the total body of reviews. During the product's lifecycle, competitors may also compare their own products with other products, resulting in performance assessments of both their own product and competitive products.

If the performance reported in more recent scientific reviews is higher than the average performance reported in the past, the firm may want to communicate its advantage (Ippolito and Mathios 1990). An increasing valence enables the firm to communicate a stronger message, which provides the firm's audience, users and experts, with more positive information on the product's performance. Hence, firms have a strong incentive to increase marketing expenditures to both users and experts. In addition, an increase in valence of scientific reviews over time also enhances the firm's confidence in the product,

allowing marketers to get higher marketing budgets to support the product. Hence, we posit the following hypothesis,

H_1: A higher valence of the body of scientific reviews leads to a) an increase in marketing expenditures to users and b) an increase in marketing expenditures to experts.

Scientific reviews on a science-based product are a technical assessment of the product's quality. Higher valence may signal higher product quality or actually confirm the underlying product quality. Product quality is shown to be positively related to sales (Tellis, Yin and Niraj 2009). Thus, more positive scientific reviews on a science-based product may increase its sales. Indeed, in the few studies relating information from scientific reviews to sales, it is the only summary measure used and generally has a positive effect on sales (Azoulay 2002; Ching and Ishihara 2010; Chintagunta, Jiang and Jing 2009; Cockburn and Anis 2001). Hence we propose:

H_2: A higher valence of the body of scientific reviews leads to an increase in sales.

Impact of Dispersion of Scientific Reviews on Marketing Expenditures and Sales

Dispersion of reviews refers to the variance across scientific reviews (Godes and Mayzlin 2004; Sun 2010; Zhu and Zhang 2010). If multiple reviews report consistent, respectively inconsistent, performance, the dispersion is low, respectively high. Dispersion of reviews may have several origins, such as the source of the review (e.g. manufacturer, competitor or independent researchers) or the testing conditions.

Prior research suggests that reviews sponsored by manufacturers are more likely to favor their product, because they choose to fund research projects with a higher likelihood of positive results (e.g. involving a weaker competitor or a more favorable testing condition) and may choose to stop a review before completion if initial results are unfavorable (Lexchin et al. 2003). On the other hand, independent researchers or competitors may have an incentive to balance these positive outcomes by testing the product in less favorable conditions. For example, the real life of a rechargeable electric car battery can differ greatly from the manufacturers' claims because of differences in parameters like vibration, shock, heat, cold, and sulfation of their lead plates, each of which may differ from the laboratory test conditions.

An increasing dispersion across scientific reviews increases the complexity of product information, which may trigger the firm to change its marketing expenditures,

either to promote aggressively or defend passionately. Reviews deviating positively from past reviews may be heavily promoted, while reviews deviating negatively may require the communication of more detail on the specific (e.g. unfavorable) testing conditions. However, firms realize that users and experts may differ in their absorptive capability of increasingly dispersed information.

Experts are more interested in the scientific information about the product, while users may consume the product with a more limited knowledge of the underlying complexities (John, Weiss and Dutta 1999). Whereas the increase in uncertainty, caused by higher dispersion across reviews, can be explained to experts to ensure they understand the implications of the different review designs on effectiveness, it may not be optimal to inform the less-educated user in a similar fashion as they have often difficulties in processing scientific information on the product (cf. France and Bone 2009). Therefore, with increasing information complexity, driven by higher dispersion, the firm may increase its marketing expenditures to experts, while decreasing its marketing expenditures to users. While experts have a high absorptive capacity and can be informed by face-to-face sales calls force under increasing dispersion, informing users, often through mass media, becomes exceedingly difficult. Hence we propose that,

H_3: A higher dispersion of the body of scientific reviews leads to a) a decrease in marketing expenditures to users and b) an increase in marketing expenditures to experts.

Higher dispersion may signal higher uncertainty about the quality of the underlying product and a higher perceived heterogeneity in product performance under different circumstances. For example, if scientific reviews of a drug contradict each other, physicians may abstain from prescribing the drug and patients may refrain from using the drug. Whatever the reasons for higher dispersion, the increase in contradictory reports over time may lead to higher skepticism among customers and lower sales (Dellarocas, Awad and Zhang 2004; Chintagunta, Gopinath and Venkataraman 2010; Moe and Trusov 2011; Zhu and Zhang 2010). Hence we propose that,

H_4: A higher dispersion of the body of scientific reviews leads to a decrease in sales.

The Impact of Volume of Scientific Reviews on Marketing Expenditures and Sales

Volume of reviews refers to the total number of reviews available (Basuroy, Chatterjee and Ravid 2003; Chevalier and Mayzlin 2006; Eliashberg and Shugan 1997; Liu

2006). A higher volume of reviews implies a larger amount of information on the product's quality (Liu 2006), especially as scientific reviews are unlikely to be published without any new information. The higher volume of the body of scientific reviews may also serve as a signal of the scientific credibility of the product to the users (McFadden and Train 1996). Each review creates an opportunity for the firm to inform the customers of the new findings. If the new findings support earlier findings, they help to strengthen the positioning; if the new findings contradict earlier findings, they need to be put in perspective and explained to both the users and experts.

Users and experts may react different to a higher volume of scientific reviews. To users, a higher volume of the body of scientific reviews enhances the salience of the product. Firms increase their marketing expenditures during these times to synchronize their marketing messages to be in line with new information being released through the scientific reviews. The higher levels of salience are also optimal times to achieve higher brand switching. On the other hand, to experts, a higher volume of reviews may yield new incremental information about the performance of the product in different conditions, some of which may be uncommon, complicated, or applicable to only special circumstances. These incremental findings may be of special interest to experts only and increased marketing expenditures to experts can help to inform the experts. To summarize, even though the messages delivered to users and experts may differ, as the volume of reviews increases, firms increase the marketing expenditures. Hence, we propose that,

H_5: A higher volume of the body of scientific reviews leads to a) an increase in marketing expenditures to users and b) an increase in marketing expenditures to experts.

The number of reviews on a product may increase the awareness and salience (exposure) of a product, which may, in turn, enhance customers' preference for the product and enhance sales (Dellarocas, Awad and Zhang 2004; 2007; Dhar and Chang 2009; Duan, Gu and Whinston 2008; Eliashberg and Shugan 1997; Liu 2006; Moe and Trusov 2011). This effect is likely to be enhanced by the increased word of mouth that occurs through the publication of new reviews. This word of mouth occurs both online and offline and is facilitated by the attention that these scientific reviews often receive in the press. A higher volume of scientific reviews also signals higher market potential to consumers, which may influence their likelihood to buy the product. Taken together, these arguments imply the following,

H_6: A higher volume of the body of scientific reviews leads to an increase in sales.

Institutional Context and Data

We test the hypotheses posited above in a prominent science-based industry (Narin 2000; Stremersch and Van Dyck 2009), namely the pharmaceutical industry. Regulatory bodies demand scientific reviews before commercialization given the potential impact on public health of pharmaceutical drugs. Such reviews pre-commercialization are later followed by many post-launch reviews, for instance, to test the drug on larger or different patient samples, to test new administration methods or dosages of the same drug, and the source of the reviews (e.g. manufacturers) may have a financial stake in the drug. The reviews may be conducted by the manufacturer, by competing manufacturers, or by independent researchers.

We focus on one important therapeutic category in the pharmaceutical industry, i.e. statins, which are drugs prescribed to patients with high cholesterol. Cholesterol can cause the buildup of plaque on the inside walls of arteries. Plaques can grow large enough to significantly reduce the blood flow through an artery. But most of the damage occurs when plaques become fragile and rupture. Plaques that rupture cause blood clots to form that can block blood flow. If such clots block a blood vessel that feeds the heart, a heart attack may occur. If it blocks a blood vessel that feeds the brain, a stroke may occur. And if blood supply to the arms or legs is reduced, it can cause difficulty walking and eventually gangrene or issue death.

Statins represent the biggest therapeutic category in the U.S. in dollar sales (Donohue, Cevasco and Rosenthal 2007). Statins (HMG-CoA reductase inhibitors; ATC: C10AA) influence the rate-limiting enzyme in cholesterol synthesis and, thereby, lower excessive cholesterol levels in the blood, particularly low density lipoprotein (LDL) cholesterol.

Reviews show that, to a minor extent, they may also increase high density lipoprotein (HDL) cholesterol and decrease excessive triglyceride levels, while expert interviews with physicians revealed limited benefits in practice. To achieve HDL increase and triglyceride decrease, physicians may use other classes of drugs, such as Omega-3 fatty acids or niacin for HDL and, fibrates or niacin for triglycerides, possibly in combination with a statin (for LDL reduction). For this reason, this paper will focus on

LDL reduction as the primary product performance measure for statins.[25] LDL reduction is expressed as the level of LDL in patients at the end of a clinical review over the LDL in those same patients at the start of the clinical review. LDL reduction is an exact measure of product performance. Except for medical meta-analyses, Cockburn and Anis (2001) is the only study in the marketing or economics literature that also uses the exact outcomes in scientific reviews.[26]

Lovastatin was the first statin to be commercialized under the name Mevacor in 1987 by Merck & Co. Over time, new statins entered the market: Pravastatin (by Bristol-Myers Squibb and marketed under the name Pravachol), Simvastatin (by Merck & Co and marketed under the name Zocor), Fluvastatin (by Novartis and marketed under the name Lescol), Cerivastatin (by Pfizer and marketed under the name Baycol), Atorvastatin (by Pfizer and marketed under the name Lipitor), and Rosuvastatin (by AstraZeneca and marketed under the name Crestor).[27] We collect reviews of the seven main drugs in this category (approval dates in parenthesis): Lovastatin (1987), Pravastatin (1991), Simvastatin (1991), Fluvastatin (1993), Atorvastatin (1996), Cerivastatin (1997), and Rosuvastatin (2003). Pitavastatin was excluded as it is not approved in the U.S yet, at the time this study was conducted.

Scientific Reviews

The data we gathered for this study is drug performance reported in clinical trials at various stages of its development and commercialization, by both manufacturers and independent researchers, from the category's inception in 1982 until 2007. To inventory all scientific reviews for statins, we use electronic bibliographic databases, such as Medline, EMBASE, the Cochrane Database of Systematic Reviews (CDSR), the Cochrane Central Register of Controlled Trials (CCTR), the Database of Abstracts of Reviews of Effects (DARE), the Science Citation Index, the NHS Economic Evaluation Database (NHS

[25] We acknowledge recent reviews (e.g. Liao and Laufs 2005) that show so-called pleiotropic effects of statins beyond LDL reduction (i.e., anti-inflammatory properties). It is suggested that especially such pleiotropic effects of statins would explain the decrease in mortality statins cause.

[26] Drug effectiveness has been measured in the literature using two other types of data. First, perceived measures are used that operationalized product quality as a composite measure of multiple dimensions like patient satisfaction and indicators of drug effectiveness (e.g. Berndt et al. 2002; Gatignon, Weitz and Bansal 1990; Hahn et al. 1994; Shankar 1999; Shankar, Carpenter and Krishnamurti 1999). However, perceived quality provides only subjective information on drug quality and already incorporates the effects of marketing. Second, several studies derive summary measures of clinical reviews to rate drug quality at introduction or over time. They categorize the results of clinical reviews as positive, negative or neutral (Azoulay 2002; Ching and Ishihara 2010, Chintagunta, Jiang and Jin 2009). Summarizing studies in such a manner provides a time-varying measure of effectiveness but ignores information from clinical reviews.

[27] Recently, reviews have also cited red yeast rice as a purely natural statin. The substance has been used in the East for many hundreds of years and its usage, based on casual observation, is also increasing in the U.S. and all around the world. Precise data is unavailable, because red yeast rice is sold both as a drug and as dietary supplement, in various formulations.

EED), and the Health Technology Assessment Database (NHS HTA). We also searched all medical journals that belong to the top 25 percentile by impact factor (62 journals in total) of all medical journals in the following four International Surveys Industry (ISI) categories: cardiac and cardiovascular systems, critical care medicine, internal medicine, and peripheral vascular disease. We limit our search to the top percentile of journals to include only high quality reviews. We limit the sample to the top journals by impact to ensure we only retain reviews of high quality.

Within these 62 journals, we searched for all articles that discussed at least one statin. We included two types of scientific reviews typical to the pharmaceutical industry - clinical studies and meta-analyses. We excluded two types of reviews: (1) reviews that do not provide the effectiveness of the drug versus a placebo, as we will use this placebo comparison as a base level to measure effectiveness (without such base level, we cannot calculate valence or dispersion of scientific reviews); (2) reviews of multi-interventional therapies (e.g. statins and fibrates) where the independent effect of the drug could not be separated out from the combined effect. For each review, we collected the time of publication and also other detailed information on its characteristics. We used two coders to extract data from the reviews using a standardized form. We also checked for consensus by having the coders code a random sample of reviews independently. Collection of a comprehensive body of scientific reviews on the category took almost two years due to the intricate process and complex nature of the content in the reviews. We also checked for a publication lag, i.e. the difference between completion of a review and its publication, but this time lag is relatively small for scientific reviews on statins. Thus, the publication date is a reasonable measure of the time the findings of the review become available to users and experts.

Sales and Marketing Data

To relate scientific reviews on statins to marketing expenditures and sales, we obtain quarterly U.S. data from IMS Health on marketing expenditures to experts and sales between 1997 and 2007 for each of the seven drugs. Sales are measured in thousands of kilograms per drug and are measured at the wholesale level (which is a close approximation for the prescriptions written during that period). Marketing expenditures to experts is measured as the sum of sales force expenditures towards physicians and advertising in journals aimed at physicians. Marketing expenditures to users is measured as the direct-to-consumer advertising expenditures for every drug, obtained from Kantar Media.

Descriptives

We identified 171 reviews from a total of 663 scientific reviews that gave specific and empirical results on effectiveness measures (the reduction in LDL levels). We extracted a total of 470 unique drug-dosage combinations from these reviews. We distinguish three different sources of the reviews. We classify a review as manufacturer-sponsored if the authors declare a link between the review and the drug manufacturer (this is a legal requirement in the pharmaceutical industry). We classify a review as competitor sponsored where a competitor performs a review on a drug, often for comparison with their own drug. We classify a review as independently sponsored if the review states that it is sponsored by a university, an entity not related to the manufacturer or if no mention is made of any financial sponsorship.

Valence, dispersion and volume: The reported performance of a product may differ substantially across scientific reviews. Table 3.1 summarizes the entire body of scientific reviews per drug. Next to the maximum and minimum performance it reports the valence, dispersion and volume. Valence is computed as the mean effectiveness (percentage LDL reduction) of a drug over all scientific reviews available up to that point in time. Figure 3.1 shows the LDL reduction with simvastatin each review reports in the respective time frame, split according to the different sources of the review, i.e. manufacturer, competitor and independent. It shows that the differences across reviews are relatively independent of simvastatin's stage in the lifecycle.

Dispersion is computed as the standard deviation around the mean effectiveness, based on all scientific reviews available up to that point in time. Figure 3.2 shows the distribution of LDL reduction with simvastatin across the three different sources of scientific reviews. For all reviews and sources the distribution is approximately normal. The differences across reviews for simvastatin are large, from as low as 15.5% LDL reduction to as high as 55% and a mean around 37%. We observe similar patterns for other statins as well (see Table 3.1). The distribution of manufacturer-sponsored reviews shows the highest mean, followed by the independent reviews and the competitor sponsored reviews. Competitor-sponsored reviews show the lowest dispersion for a majority of the drugs.

Volume is the cumulative number of scientific reviews available up to that point in time. Figure 3.3 shows the evolution in the volume of reviews for simvastatin. It shows a typical pattern for scientific reviews, where manufacturer-sponsored reviews appear first, followed by independent reviews, while competitor-sponsored reviews only appear after a competing drug has received market approval. For example, we observe a steady stream of reviews over the life cycle of Simvastatin interspersed with some jumps before its approval

by the FDA in 1991 and around the introduction of competitor atorvastatin in 1997 and the entry of rosuvastatin in 2003 (see Figure 3.3).

Each scientific review can be characterized by its design. We extract various design characteristics of the study for each drug, which are shown in Table 3.2. The dosages are very comparable across drugs, except for cerivastatin which has a different range. The clinical reviews range from 1 to 312 weeks, with an average of 34 weeks across all drugs. The number of patients enrolled in a study also widely varies, ranging from 2 to 24,000, with an average of 1,140. From Table 3.2 it is also clear that clinical study with the highest number of patients has compared five of the seven drugs. Each drug also has multiple reviews from all three sources. Table 3.2 gives the number of reviews for each drug split to their source. In our sample, 35% of the reviews are sponsored by a manufacturer. This illustrates that manufacturers are actively developing and designing reviews to build scientific information on their drugs, not only prior to approval (phase 1-3 clinical trials) but also after approval (stage 4 post marketing studies). We find that manufacturer sponsored reviews reported the minimum performance among all three sources of reviews in only 1 out of 7 statins. On average, manufacturer sponsored reviews report a 14% higher performance than competitor sponsored and independent reviews. The results on dispersion are relatively equal over all statins and sources. The volume of manufacturer and independent sponsored reviews are the largest, while the number of competitor sponsored reviews is relatively small. Later entrants perform a larger number of competitor sponsored reviews to benchmark and showcase their superiority over existing products.

Model

We develop a vector autoregressive model with exogenous variables (VARX) (Dekimpe and Hanssens 1999) to estimate the effects of valence, dispersion and volume of the body of scientific reviews on sales, marketing expenditures to users and marketing expenditures to experts. The model accounts for the endogeneity of marketing expenditures. We test for unit roots and possible cointegration relations before estimating the model. In addition, we select the optimal lag length for the VAR model. These steps are performed as follows (see for detailed discussions Grewal et al. 2000; Nijs et al. 2001):

(i) *Test for unit roots*. We conduct an Augmented Dickey Fuller (ADF) test on the three dependent variables, sales, marketing to users and marketing to experts, whereby we control for a possible intercept and deterministic trends (Dickey and Fuller 1979). We also

test for the presence of potential structural breaks, as ignoring their presence influences the results of the ADF test in favor of a unit root (Perron 1989; Zivot and Andrews 1992).

(ii) *Test for cointegration.* If a unit root of the same order is found in more than one variable, we perform a cointegration test for the existence of a long-term equilibrium among the integrated variables. Not accounting for possible cointegration results in a loss of long-term information and biases the estimates. We use the Johansen cointegration test and compare the trace test statistic or the maximum eigenvalue test statistic to its critical values (Johansen and Juselius 1990). If a cointegration relation is found, we estimate a vector error correction model (VECM), which includes the underlying long-run relations between the integrated variables (Dekimpe and Hanssens 2004).

(iii) *Lag length selection*. The results for the unit root test, the cointegration test and the final model are also dependent on the number of lags included in the model. We select the appropriate number of lags by the Bayesian information criterion (BIC) (Paulsen 1984; Pauwels, Hanssens and Siddarth 2002).

Based on the resulting model, we calculate generalized impulse response functions (GIRF) to compute the dynamic effects of marketing to users and marketing to experts on sales and vice versa. The GIRF measures the time profile of a shock to one dependent variable on future values of the other dependent variables at any given point in time (Pesaran and Shin 1998). The approach is invariant to the ordering of the variables in the model.

The exact specification of the sales response model depends on the outcomes of the unit root and cointegration tests and hence we present our time series model below as a VECM, as its representation contains the VAR model (for a detailed discussion of the model structure see Engle and Granger 1987; Nijs et al. 2001). We estimate the model using log-transformed variables as the parameters can then be interpreted as elasticities. The VECM(P) model for sales, marketing to users (M2U) and marketing to experts (M2X) for product j at time t is specified as follows:

$$\begin{bmatrix} d\log(Sales_{jt}) \\ d\log(M2U_{jt}) \\ d\log(M2X_{jt}) \end{bmatrix} = \begin{bmatrix} \alpha_{Sales} & 0 & 0 \\ 0 & \alpha_{M2U} & 0 \\ 0 & 0 & \alpha_{M2X} \end{bmatrix} \begin{bmatrix} e_{Sales} \\ e_{M2U} \\ e_{M2X} \end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix} \beta_{11}^{p} & \beta_{12}^{p} & \beta_{13}^{p} \\ \beta_{21}^{p} & \beta_{22}^{p} & \beta_{23}^{p} \\ \beta_{31}^{p} & \beta_{32}^{p} & \beta_{33}^{p} \end{bmatrix} \begin{bmatrix} d\log(Sales_{j,t-p}) \\ d\log(M2U_{j,t-p}) \\ d\log(M2X_{j,t-p}) \end{bmatrix} +$$

$$\begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix} \begin{bmatrix} d\log(Valence_{jt}) \\ d\log(Dispersion_{jt}) \\ d\log(Volume_{jt}) \end{bmatrix} + \begin{bmatrix} \delta_{11} & \delta_{12} & \delta_{13} & \delta_{14} & \delta_{15} & \delta_{16} \\ \delta_{21} & \delta_{22} & \delta_{23} & \delta_{24} & \delta_{25} & \delta_{26} \\ \delta_{31} & \delta_{32} & \delta_{33} & \delta_{34} & \delta_{35} & \delta_{36} \end{bmatrix} \begin{bmatrix} Atorvastatin_j \\ Fluvastatin_j \\ Lovastatin_j \\ Pravastatin_j \\ Rosuvastatin_j \\ Simvastatin_j \end{bmatrix} + \quad (3.1)$$

$$\begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \\ \phi_{31} & \phi_{32} \end{bmatrix} \begin{bmatrix} Intro\_Rosu_j \\ Withdrawal\_Cer_j \end{bmatrix} + \eta_{jt},$$

with P indicating the total number of lags and $d$log indicating that we take first differences from the log-transformed variable. When no unit root is found for one or more endogenous variables, the model is estimated for those variables in logs instead of first differences of the logs. In case evidence for cointegration is found, the first term on the right-hand side of the equation represents the error correction terms. α constitutes the speed of adjustment to the long-term equilibrium level for each of the three endogenous variables. e is the error correction term resulting from a regression of each endogenous variable on the other endogenous variables (possibly including an intercept and deterministic trend terms). β represent the autoregressive parameters and $\eta_{jt} \sim MVN(0,\Sigma)$. In case the dependent variables contain a unit root of the same order but are not cointegrated, e drops out of the model.

The variables in Equation (3.1) are operationalized as follows:

$Sales_{jt}$	=	Sales (in 000's of kg) for product j at time t
$M2U_{jt}$	=	Marketing expenditures (in $ 000's) to users for product j at time t
$M2X_{jt}$	=	Marketing expenditures (in $ 000's) to experts for product j at time t
$Valence_{jt}$	=	Mean performance of product j across all scientific reviews over all periods up to time t
$Dispersion_{jt}$	=	Standard deviation in performance of product j across all scientific reviews over all periods up to time t
$Volume_{jt}$	=	Number of scientific reviews on product j over all periods up to time t
$Atorvastatin_j$	=	Dummy for atorvastatin, 0 otherwise
$Fluvastatin_j$	=	Dummy for fluvastatin, 0 otherwise

$Lovastatin_j$	=	Dummy for lovastatin, 0 otherwise
$Pravastatin_j$	=	Dummy for pravastatin, 0 otherwise
$Rosuvastatin_j$	=	Dummy for rosuvastatin, 0 otherwise
$Simvastatin_j$	=	Dummy for simvastatin, 0 otherwise
$Intro\_Rosu_t$	=	Dummy for rosuvastatin which is 1 at the quarter of its introduction, 0 otherwise
$Withdrawal\_Cer_t$	=	Dummy for cerivastatin which is 1 at the quarter of its withdrawal, 0 otherwise

The length of our data series does not allow us to estimate product-specific parameters. We include product-specific intercepts in the model, which represent a trend as the dependent variables are in first differences, to capture life cycle effects of the products. For identification, we keep cerivastatin as a base product. Our model also controls for two events that have a one-time impact on the data, namely the introduction of Crestor (rosuvastatin) in the third quarter of 2003 and the withdrawal of Baycol (cerivastatin) in the third quarter of 2001.

Note that the above model allows us to obtain causal effects of scientific reviews on marketing expenditures and sales. Establishing a causal effect using econometric models can be challenging as explained in the user and expert reviews literature (Duan, Gu and Whinston 2008, Godes and Mayzlin 2004; Liu 2006). We model the relation between scientific reviews and sales and marketing in first differences. This implies that different outcomes across scientific reviews over time have a contemporaneous effect on sales and marketing. One important difference between scientific and user reviews, however, is that it takes substantially more time to perform a scientific review (typically 34 weeks in our sample) and to get it published. Hence, a contemporaneous effect of sales on scientific reviews is unlikely and makes us confident that we obtain causal effects of scientific reviews on sales and marketing expenditures.

Results

We first discuss the model specification tests, followed by the hypotheses testing and the assessment of the robustness of our results.

Model Specification

To model the relation between the valence, dispersion and volume of the body of scientific reviews, sales and marketing expenditures to users and experts, we use all quarters within our dataset in which a drug is available on the market (N=231). We find evidence of unit roots in sales, marketing to users and marketing to experts. The

augmented Dickey-Fuller test fails to reject the null hypothesis that a unit root is present, with the test statistic taking the values of 3.49 (p = 1.00) for sales, -1.96 (p = .30) for marketing to users and -1.92 (p = .32) for marketing to experts. We do not find significant evidence of one or more structural breaks in the data.

In the second step, we test for cointegration, using the Johansen cointegration test. The trace statistic rejects that the cointegration rank equals at most 0 (97.39, p = .00), while it cannot reject that the cointegration rank equals at most 1 (7.89, p = .25). In other words, sales, marketing to users and marketing to experts are cointegrated, which prompts the use of a VEC model (Dekimpe and Hanssens 1999; 2004). For the various models discussed below, we have also tested for the optimal lag length based on the BIC. The results indicated that 1, 2 or 3 lags performed best, depending on the criterion used and the exact model. As the information criteria and the direction and size of the main results for these lag lengths were quite similar, we select 1 lag for the models we present below for parsimony. Finally, we inspect and test all the models below on significant autocorrelation. We find minor autocorrelation in sales, but none for marketing to users and marketing to experts, which we interpret as evidence for a stable model specification.

Table 3.3 shows the results of our VEC(1) model on sales, marketing to users and marketing to experts. We find evidence for one cointegration relation. The following linear relation between the endogenous variables and a constant is stationary: $-28.19 + 1.00 \cdot \log(Sales_{jq}) - 2.29 \cdot \log(M2U_{jq}) + 3.07 \cdot \log(M2X_{jq})$. Thus, in the long term, these variables are in equilibrium according to this relation. The log-transformation of the cointegration function allows us to interpret this in terms of changes in percentage. The cointegration relation implies that a 1% increase in kg sales of a drug leads in the long run to a 2.29% increase in marketing expenditures to users and to a 3.07% decrease in marketing expenditures to experts. The speed of adjustment of the long term equilibrium is given by the error correction parameters. These are between -.07 and .11, indicating that the adjustment is slow.

To compute the effects of marketing to users and marketing to experts on sales, we compute the GIRF and we find an immediate elasticity for marketing to users of .03 and an immediate elasticity for marketing to experts of.18. This means that a 1% increase in marketing to users increases the kilogram sales in that same quarter by .03% but the same percentage increase in marketing to experts increases the kilogram sales by.18%. Due to the cointegration relation, we also find that 68% of the increase in marketing to users is sustained in the long run, but only 51% of the increase in marketing to experts is sustained in the long run. This sustained increase in marketing expenditures has a permanent elasticity of .05 for marketing to users and of .16 for marketing to experts.

Impact of Scientific Reviews on Sales and Marketing

Considering the effects of the valence, dispersion and volume of the body of scientific reviews on sales and marketing expenditures to users and experts, we find that 7 out of 9 parameters are significant[28]. We can use these estimates to test our hypotheses. Confirming H_{1a} and H_{1b}, we find that the valence of the body of scientific reviews indeed increases the marketing expenditures to both users ($t = 2.7$) and experts ($t = 2.1$). Confirming H_2, we find that the valence of the body of scientific reviews increases sales ($t = 2.9$).

Confirming H_{3a} and H_{3b}, we find that a higher dispersion of the body of scientific reviews leads to a decrease in marketing expenditures to users ($t = -3.3$) and an increase in marketing expenditures to experts ($t = 3.1$). Contrary to H_4, we find that a higher dispersion of the body of scientific reviews does not lead to a decrease in sales ($t = -1.3$). Possibly two contrary effects may be at play. On the one hand, a high dispersion may cause uncertainty regarding performance (i.e., scientific reviews disagreeing on the LDL reduction under the same condition) leading to a decrease in sales. On the other hand, a high dispersion also may reflect the usage of the same product under different conditions (i.e., increasing the number of indications or the addressable market for statins) leading to an increase in sales. In our sample, both effects may cancel out.

Contrary to H_{5a}, we do not find a significant effect of the volume of the body of scientific reviews on the marketing expenditures to users ($t = 1.0$). Confirming H_{5b}, we find that a higher volume of the body of scientific reviews increases the marketing expenditures to experts ($t = 2.2$).

Confirming H_6, we find that a higher volume of the body of scientific reviews increases sales ($t = 1.9$).

Robustness

We test the robustness of our results in multiple ways. First, we estimated VEC models of higher order, which showed similar fit statistics. While the main results are shown for a VEC(1) model, the theoretical inference for all hypotheses are the same for a VEC(2) and a VEC(3) model. For illustrative purposes, we show the results for the VEC(2) model in Table 3.4, which has higher log likelihood (-677.21) than the VEC(1) model.

Second, we have tested various operationalizations of the summary metrics of scientific reviews. In our current model, we used all available reviews from the past in the

[28] To test our directional hypotheses we use a one-sided test with α=.05. This means that t-values above 1.65 are significant.

construction of the measures. We have estimated the same model, whereby we computed the valence, dispersion and volume as a moving average over the last 24, 20, 16 and 12 quarters. For illustrative purposes, we show the results for moving average 16 quarters in Table 3.5, which has lower log-likelihood (-694.70) than in our main model in Table 3.3. While we only show the model for 16 quarters, the outcomes the models with moving averages over more than 16 quarters confirm the robustness of our theoretical inference. For moving averages over shorter periods (e.g. 12 quarters), the outcomes are not stable as few scientific reviews appear in smaller time periods for some brands.

Third, we tested the robustness of our results to the choice of functional form for our model. In our current model, we use log-transformed variables. We estimated a similar model in levels, which also contained unit roots for sales, marketing to users and marketing to experts. The results from such model led to the same theoretical inference as the model reported in Table 3.3. We tested the inclusion of various control variables, such as the time the drug has been on the market and seasonality (by including three quarter dummies). The theoretical inference from a model including such control variables and the model reported in Table 3.3 is the same. Further, we estimated the model using molecules other than cerivastatin as the base brand, as cerivastatin was withdrawn from the market in the middle of the sample period because of unacceptable levels of side effects. We find that our results are robust to the choice of the base brand.

Fourth, we have found evidence that scientific reviews affect both sales and marketing expenditures, omitting scientific reviews from the sales response model may lead to biased parameter estimates for the responsiveness of sales to marketing expenditures. If the dimensions we use to summarize the body of scientific reviews affect both marketing expenditures and sales positively (negatively), then excluding scientific reviews leads to an overestimation (underestimation) of the effect of marketing on sales. Table 3.6 shows a model that omits the valence, dispersion and volume of the body of scientific reviews from the model of which we presented the estimates earlier in Table 3.3. It has a log likelihood of -700.39, implying a lower fit than in the model with scientific reviews. In a model omitting the valence, dispersion and volume of the body of scientific reviews, the immediate elasticity of marketing to users is 6% higher and the immediate elasticity of marketing to experts is 17% higher, as compared to their respective elasticities in the model of which the estimates are presented in Table 3.3. The permanent effect of marketing to users, respectively experts, is overestimated by 7%, respectively 19%. Also in all models we estimated for robustness analysis as reported here above, the effect of marketing is overestimated when scientific review variables are not included.

Implications

The cumulative information based on scientific reviews changes significantly over time and is an important element in science-based industries. The different metrics of the body of scientific reviews have substantial effects on sales and marketing decisions. We conclude that scientific reviews are an important element of the marketing mix, which has three important implications for firms and researchers.

First, our findings allow firms to anticipate and counteract marketing strategies of competitors given the results of a scientific review of a competitive product. For example, in the last quarter of 2002, three different scientific reviews of atorvastatin were published (for a total of four different patient populations). The valence reported in these reviews was lower than the valence reported in the past and affected the dispersion negatively. Sales of atorvastatin grew on 2% in that quarter,lower than the median growth during our data period of 3.5%. The manufacturer of the drug, Pfizer, reacted by decreasing the marketing expenditures substantially to users in that quarter to the lowest level in four years. While the marketing expenditures to experts decreased as well during that time, the decrease was comparatively modest. Combining the impact of the three different metrics, Pfizer's reaction seems in line with our conclusions. Pfizer reacted to adverse new information from independent researchers about the performance of its products by making adjustments to both the total marketing expenditures and the allocation of the expenditures between users and experts. In the future, competitors may benefit from anticipating such a reaction from the focal firm by intensifying their own marketing efforts during such times. In this particular example, Bristol-Myers Squibb reacted in that quarter by spending the highest amount on marketing towards users ever for Pravastatin. Thus, our findings create higher insights for product managers in pharmaceutical firms to understand and react to marketing strategies of competitors.

Second, our method and study provides insights on the value of a scientific review on sales. For example, a scientific review comparing the effectiveness of the higher dosage atorvastatin with a lower dosage simvastatin sponsored by Parke Davis (a subsidiary of Pfizer, the manufacturer of atorvastatin) was published in the first quarter of 2001 in The Lancet (Smilde et al. 2001). The outcomes were above average for atorvastatin and increased the total dispersion over all available reviews up to that point in time. During that quarter, the sales of atorvastatin increased by 5.3%, direct-to-consumer advertising decreased by 5.7% and detailing increased by more than 25%. Firms can also use our model to assess the return on investments in conducting scientific reviews. In the example above, we estimated the impact of this scientific review on sales as the difference

in sales in the same period with and without the publication of that scientific review. This method suggests that even after accounting for the changing marketing expenditures in that quarter, value of the scientific review on sales of atorvastatin was approximately $32 millions. While this example makes some simplifying assumptions including the release of a single review in a quarter and focus only on the impact for a single quarter, the results still suggest that the impact of scientific reviews on sales is significant and firms have an incentive to initiate more scientific reviews and especially those that are likely to provide more positive results. However, unlike user reviews, firms may not be able to actively manipulate scientific reviews to increase sales because the peer-review process followed in scientific journals acts as checks against fraudulent claims (Dellarocas 2006; Mayzlin 2006).

Third, we develop and propose metrics on how to analyze marketing strategy towards users and experts under conditions of changing product performance of both the focal product and competitors' products. Our results show that it is important in science-based industries to account for the changes in overall information available about product performance as new outcomes from scientific reviews appear over time. This is a typical omitted variable bias problem. We find that not including scientific reviews in the sales response model leads to an upward bias of the marketing effectiveness estimate. The implication for firms and researchers analyzing the returns on marketing expenditures in science-based industries is to specify a sales response model that includes the outcomes of scientific reviews, in addition to the marketing variables. As it can be a time-consuming task to collect all scientific reviews for a category, alternatively an econometric solution may be chosen. For example, when the outcomes of scientific reviews change over time, one can incorporate a time-varying constant in the model (Osinga, Leeflang and Wieringa 2008). The problem of omitting scientific reviews from the model is similar to the bias that arises by not correcting for time-varying product quality (Sriram, Neelameghan and Chintagunta 2006).

As we are the first to comprehensively analyze the relationship between scientific reviews, sales and marketing to users and experts, our paper has a few limitations that offer future research opportunities. First, we test our hypotheses in one industry and we would welcome future research that tests the role of scientific reviews in other science-based industries. Second, the limited number of observations per brand in our data did not allow us to test the impact of firms' marketing expenditures on marketing effectiveness. Future research can investigate whether and how the availability of scientific research impacts the effectiveness of marketing expenditures. Third, we do not know firms' objectives for running a review and how the design of a scientific review (e.g. comparison products)

affects its outcomes. Future research can investigate the use of scientific reviews as a marketing instrument against competitors.

Tables

Table 3.1: Summary Statistics of Drug Effectiveness (PercentageLDL Reduction) for all Statins and all Reviews Included in our Analysis

	Atorva-statin	Ceriva-statin	Fluva-statin	Lova-statin	Prava-statin	Rosuva-statin	Simva-statin	All
Min	6.3	11.5	15.0	17.0	15.7	28.0	15.5	15.6
Max	64.0	44.0	36.1	48.0	50.8	70.0	53.0	52.3
Valence	40.5	31.4	26.5	33.0	26.6	46.7	37.1	34.5
Dispersion	9.9	8.5	4.8	7.1	5.0	8.7	6.1	7.2
Volume	91	26	40	62	82	90	79	67

Table 3.2: Summary Statistics of Reviews for all Statins and all Reviews Included in our Analysis

Design Variable		Atorva-statin	Ceriva-statin	Fluva-statin	Lova-statin	Prava-statin	Rosuva-statin	Simva-statin
Dosage in mg	Min	10	.2	20	10	10	5	10
	Max	80	.8	80	80	80	80	80
Duration in weeks	Mean	27	38	34	48	46	14	41
	Min	2	4	6	4	1	4	2
	Max	312	104	312	312	312	312	312
Number of patients	Mean	930	882	1,773	1,692	1,307	566	1,145
	Min	2	15	12	11	5	12	2
	Max	24,000	3,113	24,000	24,000	10,355	24,000	24,000
Manufacturer funded	N	36	5	17	24	14	43	30
Competitor funded	N	21	2	8	6	19	4	15
Independent reviewer	N	34	19	15	32	43	43	34

Table 3.3: Estimation Results for the Model for Sales, Marketing to Users and Marketing to Experts (Equation 3.1)

VECM(1) with Scientific Reviews as Moving Average over All Quarters							
		Estimate	T-value				
Cointegration relation	Sales(t-1)	1.00					
	Marketing to users (t-1)	-2.29***	-8.00				
	Marketing to experts (t-1)	3.07***	7.30				
	Constant	-28.19***	-6.70				
		Sales		**Marketing to Users**		**Marketing to Experts**	
		Estimate	T-value	Estimate	T-value	Estimate	T-value
Error Correction	Error correction term	-.01*	-1.9	.11***	5.1	-.07***	-6.4
Autoregressive Parameters	Sales(t-1)	-.06*	-1.7	-.22	-.9	.12	1.0
	Marketing to users (t-1)	-.01	-.7	-.11*	-1.7	-.08**	-2.4
	Marketing to experts (t-1)	-.05**	-2.4	.24	1.6	.02	.2
Metrics for the Body of Scientific Reviews	Valence	H_2(+)		H_{1a}(+)		H_{1b}(+)	
		9.00***	2.9	27.02***	2.7	17.80**	2.1
	Dispersion	H_4(-)		H_{3a}(-)		H_{3b}(+)	
		-.39	-1.3	-6.88***	-3.3	3.27***	3.1
	Volume	H_6(+)		H_{5a} (+)		H_{5b}(+)	
		1.88*	1.9	6.54	1.0	7.41**	2.2
Control Variables	Atorvastatin	-.07	-1.2	1.39***	3.5	-.85***	-4.3
	Fluvastatin	-.01	-.2	-.10	-.3	-.02	-.1
	Lovastatin	-.01	-.3	.54*	1.8	-.44***	-2.9
	Pravastatin	-.05	-1.0	.71**	2.1	-.67***	-4.0
	Rosuvastatin	.10	1.3	1.87***	3.4	-.91***	-3.3
	Simvastatin	-.05	-.8	1.39***	3.3	-.85***	-4.0
	Introduction Rosuvastatin	1.34***	9.4	.15	.1	1.94***	3.7
	Withdrawal Cerivastatin	-3.38***	-2.7	8.96	1.0	-3.42	-.8
	N	231					
	Log likelihood	-686.11					

*P-value < .10 (one-tailed test); **P-value < .05 (one-tailed test); ***P-value < .01 (one-tailed test).

Table 3.4: The VECM Model is Robust to the Number of Lags

VECM(2) with Scientific Reviews as Moving Average over All Quarters							
		Estimate	T-value				
Cointegration relation	Sales(t-1)	1.00					
	Marketing to users (t-1)	-1.81***	4.7				
	Marketing to experts (t-1)	1.46***	-8.3				
	Constant	-11.65***	-3.7				
		Sales		**Marketing to Users**		**Marketing to Experts**	
		Estimate	T-value	Estimate	T-value	Estimate	T-value
Error Correction	Error correction term	.00	-.6	.19***	5.6	-.07***	-4.0
Autoregressive Parameters	Sales(t-1)	-.06	-1.6	-.29	-1.2	.18	1.4
	Marketing to users (t-1)	.00	-.0	.26*	1.7	-.02	-.2
	Marketing to experts (t-1)	-.06**	-2.5	.08	.4	-.20*	-1.9
	Sales(t-2)	.01	.5	-.02	-.2	-.10	-1.6
	Marketing to users (t-2)	.00	-.6	.04	.7	-.08**	-2.5
	Marketing to experts (t-2)	.00	-.4	-.06	-.8	-.07**	-2.16
Metrics for the Body of Scientific Reviews	Valence	7.68**	2.4	23.29**	2.3	24.87***	2.7
	Dispersion	-.30	-1.0	-4.55**	-2.2	2.30**	2.2
	Volume	1.97**	2.0	9.60	1.4	7.72**	2.3
Control Variables	Atorvastatin	-.01	-.2	1.23***	3.4	-.49***	-2.7
	Fluvastatin	.01	.2	-1.01***	-3.1	.31*	1.9
	Lovastatin	.03	.6	-.57**	-2.0	.10	.7
	Pravastatin	-.01	-.1	.19	.7	-.30**	-2.1
	Rosuvastatin	.15**	2.0	1.91***	3.6	-.35	-1.3
	Simvastatin	.00	.1	1.23***	3.2	-.48**	-2.5
	Introduction Rosuvastatin	1.34***	9.2	-.07	-.1	1.88***	3.7
	Withdrawal Cerivastatin	-3.32***	-2.6	6.55	.7	-1.90	-.4
	N	224					
	Log likelihood	-677.21					

*P-value < .10 (one-tailed test); **P-value < .05 (one-tailed test); ***P-value < .01 (one-tailed test).

Table 3.5: The Results for the Scientific Reviews Are Robust to the Time over which They Are Calculated

VECM(1) with Scientific Reviews as a Moving Average over 16 Quarters							
		Estimate	T-value				
Cointegration relation	Sales(t-1)	1.00					
	Marketing to users (t-1)	-7.15***	7.0				
	Marketing to experts (t-1)	8.93***	-8.5				
	Constant	-73.65***	-5.9				
		Sales		**Marketing to Users**		**Marketing to Experts**	
		Estimate	T-value	Estimate	T-value	Estimate	T-value
Error Correction	Error correction term	.00	-1.0	.04***	5.8	-.02***	-5.3
Autoregressive Parameters	Sales(t-1)	-.07*	-1.9	-.19	-.7	.13	1.0
	Marketing to users (t-1)	-.00	-.3	-.07*	-1.1	-.06*	-1.7
	Marketing to experts (t-1)	-.04**	-2.2	.16	1.2	-.01	-.2
Metrics for the Body of Scientific Reviews	Valence	1.36**	2.5	9.93*	1.8	9.50*	1.9
	Dispersion	-.07	-.7	-2.21**	-2.3	1.00**	2.0
	Volume	.31*	1.9	.44	.57	1.32*	1.81
Control Variables	Atorvastatin	.00	-.1	2.28***	5.2	-.91***	-4.0
	Fluvastatin	.00	.1	.25	.9	-.12	-.8
	Lovastatin	.00	.0	.87***	2.7	-.47***	-2.9
	Pravastatin	-.02	-.5	1.31***	3.6	-.74***	-4.0
	Rosuvastatin	.17**	2.0	2.54***	4.5	-.85***	-2.9
	Simvastatin	-.03	-.4	2.14***	4.6	-.93***	-3.9
	Introduction Rosuvastatin	1.34***	9.3	.20	.2	2.15***	4.2
	Withdrawal Cerivastatin	-3.31**	-2.5	8.67	1.0	-3.53	-.8
	N	231					
	Log likelihood	-694.70					

*P-value < .10 (one-tailed test); **P-value < .05 (one-tailed test); ***P-value < .01 (one-tailed test).

Table 3.6: Sales Response Model without Scientific Reviews

VECM(1) without Scientific Reviews							
		Estimate	T-value				
Cointegration relation	Sales(t-1)	1.00					
	Marketing to users (t-1)	-5.77***	7.6				
	Marketing to experts (t-1)	7.58***	-8.5				
	Constant	-63.95***	-6.5				
		Sales		**Marketing to Users**		**Marketing to Experts**	
		Estimate	T-value	Estimate	T-value	Estimate	T-value
Error Correction	Error correction term	.00	-1.1	.05***	5.7	-.02***	-5.7
Autoregressive Parameters	Sales(t-1)	-.07*	-1.9	-.19	-.7	.12	1.0
	Marketing to users (t-1)	-.00	-.4	-.08	-1.3	-.07**	-2.2
	Marketing to experts (t-1)	-.04*	-1.8	.17	1.3	.00	.0
Control Variables	Atorvastatin	.00	-.0	2.15***	-4.1	-.90***	5.0
	Fluvastatin	.00	-.0	.25	-.9	-.13	.9
	Lovastatin	.00	-.0	.88***	-3.2	-.52***	2.8
	Pravastatin	-.03	-.5	1.24***	-4.2	-.77***	3.5
	Rosuvastatin	.16**	2.0	2.42***	-3.0	-.87***	4.3
	Simvastatin	-.02	-.4	2.03***	-4.1	-.95***	4.5
	Introduction Rosuvastatin	1.34***	9.3	.28***	4.2	2.15*	.3
	Withdrawal Cerivastatin	-3.34**	-2.5	8.7	-.7	-3.35	1.0
	N	231					
	Log likelihood	-700.39					

*P-value < .10 (one-tailed test); **P-value < .05 (one-tailed test); ***P-value < .01 (one-tailed test).

Figures

Figure 3.1: Outcomes of Reviews over Time
(LDL Reduction with Simvastatin)

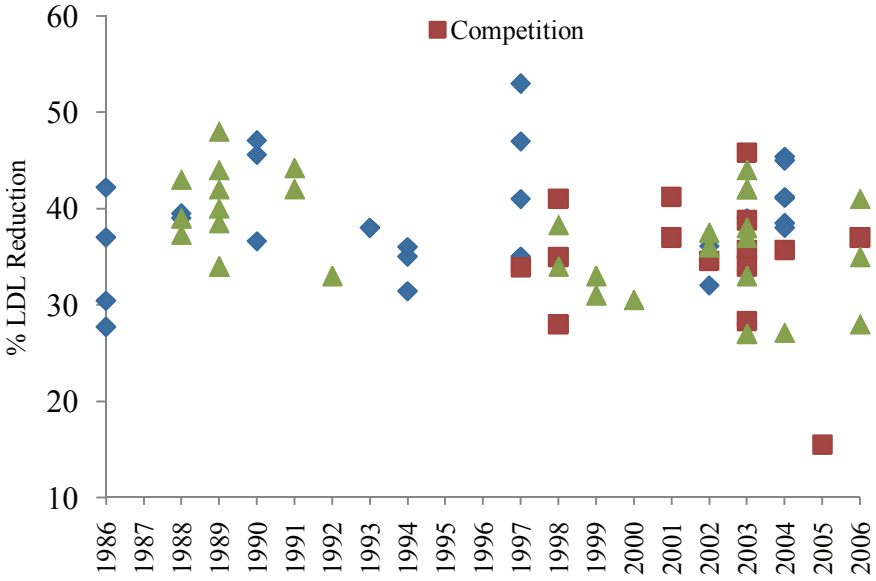


Figure 3.2: Distribution of Outcomes of All Reviews (LDL Reduction with Simvastatin)

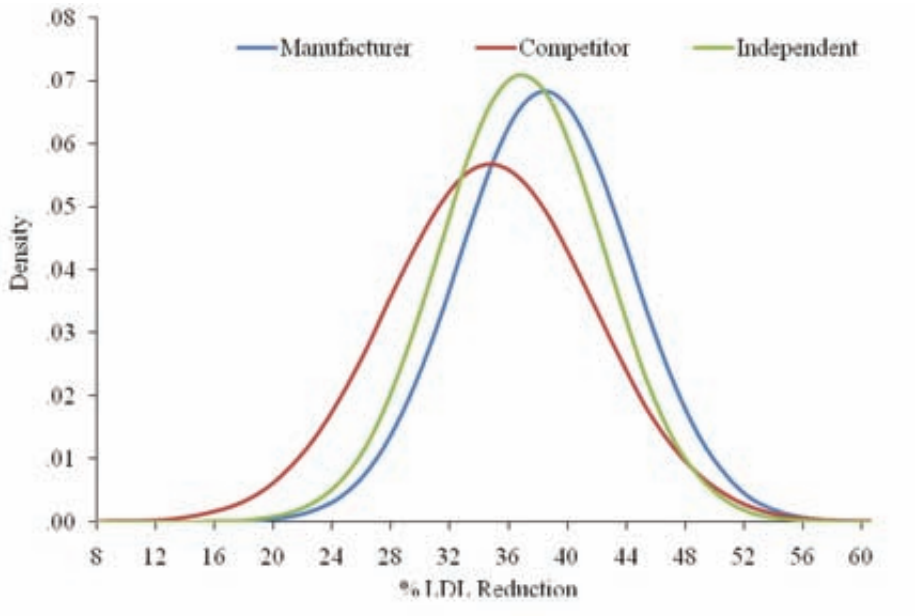
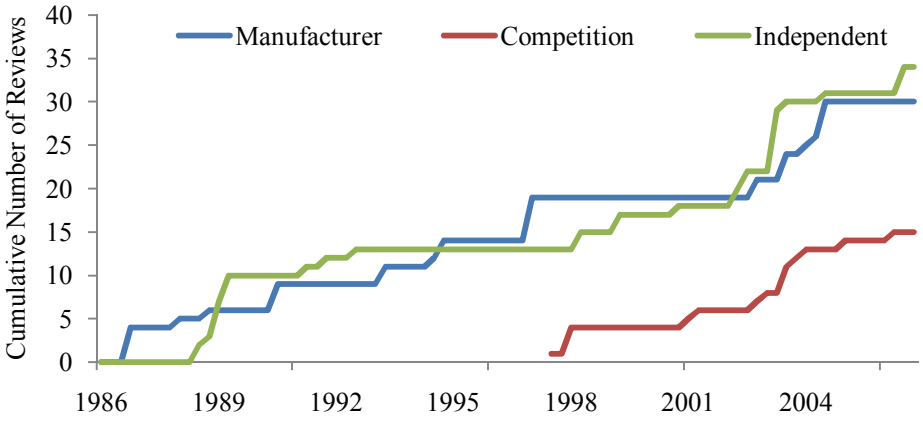


Figure 3.3: Cumulative Number of Reviews over Time by Source of Funding for Simvastatin



Conclusion of Dissertation

The pharmaceutical industry has two important characteristics differentiating it from most other industries; it is highly regulated and it has a strong link with science. These characteristics have a big influence on pharmaceutical marketing research and have served as an inspiration of the essays in this dissertation.

The essays investigate various substantial problems in the pharmaceutical industry using empirical models. The essays can be classified along two dimensions pertaining to the flow of pharmaceutical marketing and the type of data used (see Figure 0.1 in the Introduction). While most of these dimensions have been covered in this dissertation, there are many possibilities left for future research in these areas. Each essay ends with several concrete suggestions for future research, which I will not repeat here. Instead, I will discuss two main implications from this dissertation and three broader promising areas of research in pharmaceutical marketing.

Implications

Empirical pharmaceutical marketing research benefits from the enormous amounts of detailed data available. Often this data is of high quality and very structured due to the strong regulations in this industry. This has two important implications: (i) it allows in-depth industry-specific studies and (ii) it allows using the unique data from the industry to investigate generalizable marketing phenomena.

First, in-depth studies on the pharmaceutical industry are important as the industry makes up a large part of the economy and deals with an important cause, which is the health of people. Essay 2 provides a good example of this. Using an advanced empirical model, I show that positively biased information has a detrimental impact on sales call effectiveness. This is not only important for firms to improve their return-on-investment to detailing, but also suggests that firms should behave more in line with the guidelines set by the authorities, which likely benefits the health of people (although the study does not give a definitive answer to that).

Second, the structured and rich data in the pharmaceutical industry allow the researcher to uniquely investigate several marketing phenomena. These studies can build much needed theory on topics that transcend the pharmaceutical industry. For example, many theory on innovations has been build or empirically tested using pharmaceutical data, as due to the high quality of available datasets and its strong focus on R&D, it provides many real-world examples on innovations (e.g. Acemoglu and Linn 2004; Shankar et al. 1998; Sorescu et al. 2003). Essay 3 also provides an example of the

possibility to use pharmaceutical data to investigate a generalizable marketing phenomenon. It investigates the role of scientific reviews on sales and marketing in science-based industries. Similar to the role of the movie industry in developing a substantial amount of theory on user and expert reviews (e.g. Eliashberg and Shugan 1997), the accessibility of scientific reviews in the pharmaceutical industry allows empirical testing of its role and to build theory.

Future Research

In line with these implications, I suggest three important areas for future research in pharmaceutical marketing. First, more extensive and more detailed data becomes available from data providers like IMS Health, Kantar Media, SDI Health and Wolters Kluwer, which will provide new research opportunities and might require new modelling techniques. One such development is the collection of the content of pharmaceutical sales calls and advertisement. In this dissertation, I have performed an analysis of sales message content based on doctor-perceived topics discussed in the sales call. For direct-to-consumer advertising, however, databases reporting the exact content of the advertisements are available (e.g. the theme, information content, etc.) and can directly be connected to the effectiveness of the campaign. Analyzing both the content of promotional efforts towards doctors and patients might provide valuable and detailed insights in the working of pharmaceutical promotion. This might inform both companies and regulators.

Second, in my dissertation, I have limited my focus mainly on three important players in the pharmaceutical industry, i.e. firm, sales rep and doctor. However, there are many more players involved in this industry, such as patients, regulators, insurers, HMOs, etc. The omission of many of these players from the analysis is not only a limitation of my dissertation, but also applies to the pharmaceutical marketing literature in general. Future research can benefit greatly from the inclusion of multiple of these less-researched market players into the analysis, however this might also require the development of new models. An exemplary topic for this is the research into drug prices in the U.S. As this market has little regulations concerning prices, the formation of the price is influenced by several different market players, such as the firm, the insurer, patient advocacy groups and HMOs. However, a dearth of research concerning prices of prescription drugs can be observed in the literature. Illustrative of the situation, is that a relatively straightforward study of Lu and Comanor (1998) is often considered to be the most important pricing paper on prescription drugs in the U.S., while many things have changed in the market since (cf. Scherer 2004).

Finally, most empirical research on pharmaceutical marketing considers its impact on financial outcome variables, such as sales, prices and profits. However, little research empirically connects pharmaceutical marketing to health outcomes. Notable exceptions have studied the marketing impact on patient compliance (e.g. Wosinska 2005). Innovative approaches are welcome to relate pharmaceutical marketing efforts to the quality of doctors' decisions and patients' health.

Summary in English

Pharmaceutical marketing effectiveness comprises the measurement of the effect of marketing efforts of pharmaceutical firms towards doctors and patients. These firms spend billions of dollars yearly to promote their prescription drugs. This dissertation provides empirical analyses and methods to contribute to several substantial problems on pharmaceutical marketing effectiveness.

The pharmaceutical industry has two main characteristics differentiating it from other industries: (i) it is highly regulated as it deals with people's health and (ii) it is a science-based industry. These characteristics in itself make it worthwhile to investigate this industry in depth. The methods and insights developed also apply, to a certain extent, to marketing problems in other industries.

Using unique data in every essay, this dissertation studies the role of the firm, sales rep and doctor in pharmaceutical marketing. The first essay evaluates the size of the sales force and the allocation of sales calls among doctors. In particular, it provides a method to gauge a yet-to-be-enacted firm-initiated policy shift. Pharmaceutical firms invest heavily in their sales force, also referred to as detailing, and expenditures have more than doubled over the last decade to $25 billion in 2005. There is an ongoing debate in the academic literature in marketing about its effectiveness. Public policy administrators and health care providers are concerned with the social welfare implications of intensive detailing to doctors, which is also reflected in the negative public opionion on pharmaceutical marketing expenditures. In addition, multiple pharmaceutical firms such as AstraZeneca, GlaxoSmithKline and Wyeth speculate that sales forces have grown too big and some publicly announced that they are considering dramatically cutting the size of their sales force. One important reason why firms have not cut their detailing is that it is very challenging to predict the outcomes of such a drastic change in the sales force size.

In the first essay a framework is developed– called data enrichment – to gauge the implications of a firm-initiated yet-to-be-enacted policy shift, which is applied to various downward policy shifts in detailing. It requires the combination of data on revealed choices from the past with stated choices obtained from managers on the future, concerning the detailing allocation of firms under different policy shift scenarios. For example, how would a firm react if a major competitor suddenly reduces its sales force by 25% in a particular therapeutic category. The data enrichment framework not only provides valuable insights into the outcomes of a downward policy shift in detailing, but also provides a framework for future analyses of a wide range of policy shifts.

The results show that small detailing changes are not able to buck the trend of increasing sales forces, but a drastic reduction in detailing by the market leader is needed to generate a profitable market outcome for all players. The initiator of the shift is always better off and the followers show mixed outcomes on profitability. Furthermore, initiating a downward policy shift always reduces the size of the market.

The second essay studies the effectiveness of the information content provided in sales calls. It focuses on the core of the interaction between sales representative and doctor. Interestingly, the marketing literature has found large heterogeneity in pharmaceutical sales call effectiveness. While various explanations have been given for this heterogeneity no one has investigated the role of the information content provided in the sales message. The main research questions in this essay are: (1) how responsive doctors are to information provided across different product attributes; (2) whether firms present a positively biased information set to doctors; (3) whether doctors are more or less responsive to positively biased information in sales calls. This requires a model that estimates the effectiveness at the sales call level, while controlling for the possible endogeneity of sales call allocation and possibly the endogenous content of the sales call. To estimate the effectiveness at the sales call level, while controlling for endogeneity, a hierarchical Bayesian VAR model is used. Positively biased information is operationalized by linking the information content to scientific information on the drugs.

The results show that: (1) firms do not provide information on the right product attributes at their optimal frequency; (2) sales calls include discussion of positively biased information; (3) discussion of positively biased information lowers sales call responsiveness in the long term. The results suggest that firms can adjust their messaging to increase doctors' responsiveness to the sales call. At the same time, this message adjustment can ease public concerns on the discussion of positively biased information with doctors.

In the third essay, the interplay between drug sales, marketing and scientific reviews is studied in detail. The pharmaceutical market is a prototypical example of a science-based market. Products in science-based markets are largely supported by scientific reviews that appear prior to and during its lifecycle. As the outcomes of scientific reviews differ across studies and over time, this essay investigates (1) how do scientific reviews affect a firm's marketing expenditures towards users and experts, and (2) to what extent do scientific reviews affect sales. In addition, it investigates how the exclusion of scientific reviews from the sales response model, as is common in the academic literature, influences marketing responsiveness parameters.

To answer these research questions, a comprehensive dataset on scientific reviews is employed for an important category in the pharmaceutical industry and is combined with brand-level sales and marketing expenditures. To analyze the dynamic relation between sales, marketing expenditures towards users and experts and scientific reviews, a vector error correction (VEC) model is used. Three metrics are used to summarize the outcomes of the body of scientific reviews over time: valence (the mean effect of the drug across reviews), dispersion (the standard deviation of the drug effectiveness across reviews) and the volume (the number of reviews per drug).

The results show that these metrics have a significant effect on sales and marketing expenditures. Higher valence of scientific reviews increases marketing expenditures to both users and experts, while higher dispersion across scientific reviews leads to a reallocation of marketing from users towards experts. Higher volume has no effect on marketing to users, but increases marketing to experts. Product sales are positively affected by both valence and volume of scientific reviews. In addition, estimating the responsiveness of sales to marketing expenditures while omitting the various dimensions of scientific reviews leads to an upward bias in the marketing responsiveness parameter.

All essays contain a strong managerially interesting component and hence this dissertation contains valuable implications for academics and managers. For academics: (i) a new alternative to gauge policy shifts is offered; (ii) a model is offered to analyze the effectiveness of sales message content; and (iii) scientific reviews should be considered to correctly measure pharmaceutical marketing effectiveness. The implications for managers are: (i) the market leader is able to buck the trend in increasing sales forces; (ii) sales reps discuss positively biased information too often, which is counterproductive in the long run; and (iii) scientific reviews on products are actively considered as a part of the marketing mix and can be used to infer competitive strategies.

Nederlandse Samenvatting (Summary in Dutch)

De effectiviteit van farmaceutische marketing omvat het meten van de invloed van marketingacties van farmaceutische bedrijven gericht op artsen en patiënten. Deze farmaceutische bedrijven geven jaarlijks miljarden euro's uit om hun medicijnen te promoten. Dit proefschrift maakt gebruik van empirische analyses en methoden om verscheidene belangrijke en relevante problemen omtrent farmaceutische marketing te bestuderen.

De farmaceutische industrie heeft twee belangrijke eigenschappen waarmee het zich onderscheidt van andere industrieën: (i) het is in hoge mate gereguleerd omdat het direct met de gezondheid van mensen te maken heeft en (ii) het is een industrie die op de wetenschap is gebaseerd. Deze eigenschappen tonen al de relevantie van diepgravende onderzoeken in deze industrie. Echter, de methoden en inzichten in dit proefschrift hebben, in zekere mate, ook waarde voor marketingproblemen in andere industrieën.

Dit proefschrift bestudeert de rol van het bedrijf, de artsenbezoeker en de arts binnen de farmaceutische marketing. Elk essay maakt daarbij gebruik van unieke data. Het eerste essay analyseert het aantal artsenbezoekers dat een bedrijf heeft en hoe het bedrijf haar artsenbezoeken verdeeld over de artsen. In het bijzonder ontwikkelt het een methode om te voorspellen wat de consequenties zijn van een toekomstige drastische beleidsverandering die door een bedrijf wordt geïnitieerd. Farmaceutische bedrijven investeren flink in hun artsenbezoekers en die uitgaven zijn meer dan verdubbeld in het afgelopen decennium ($25 miljard in 2005). Er is een hevige discussie in de wetenschappelijke marketingliteratuur over de gevolgen van het intensief bezoeken van artsen door artsenbezoekers. Overheden en zorgaanbieders zijn bezorgd om de gevolgen van de intensivering van het aantal artsenbezoeken voor het maatschappelijk welzijn, hetgeen ook nog eens bevestigd wordt door de negatieve publieke opinie hieromtrent. Daarbovenop speculeren verschillende farmaceutische bedrijven zoals AstraZeneca, GlaxoSmithKline en Wyeth publiekelijk dat het aantal artsenbezoeken uit de klauwen is gelopen en sommige bedrijven hebben aangekondigd dat ze een drastische verlaging hiervan overwegen. Echter, een belangrijke reden waarom de meeste bedrijven dit niet in daden hebben omgezet is de grote onzekerheid over de gevolgen van een dergelijke drastische verandering.

In dit eerste essay wordt een methode ontwikkeld – *data enrichment* – die de consequenties van een drastische beleidsverandering van een bedrijf vooraf voorspeld. Deze wordt toegepast om een aantal verschillende drastische verlagingen in het aantal artsenbezoekers van een bedrijf. De methode combineert geobserveerde data uit het

verleden (*revealed preference data*) met data verzameld van managers over beslissingen in toekomstige scenario's voor een bedrijf (*stated preference data*) omtrent het aantal en de verdeling van artsenbezoeken onder artsen. Bijvoorbeeld, hoe reageert een bedrijf als een belangrijke concurrent het aantal artsenbezoekers binnen een bepaalde therapeutische categorie met 25% verlaagd. De ontwikkelde methode is niet alleen bruikbaar voor dit specifieke probleem, maar is ook bruikbaar voor toekomstige analyses van drastische beleidsveranderingen.

De resultaten laten zien dat een kleine verlaging van het aantal artsenbezoekers niet leidt tot een ommekeer binnen de industrie, maar dat een forse verlaging van de marktleider nodig is om een ommezwaai in het aantal artsenbezoekers teweeg te brengen die winstgevend is voor alle bedrijven in de betreffende markt. Daarnaast blijkt dat het bedrijf dat zijn beleid drastisch verandert altijd beter af is, terwijl de andere bedrijven gemixte resultaten laten zien. Voorts leidt een daling in het aantal artsenbezoekers altijd tot een vermindering van de totale verkopen in de productcategorie.

Het tweede essay bestudeert de effectiviteit van het soort informatie dat wordt besproken in een artsenbezoek. Het richt zich op de kern van de interactie tussen artsenbezoeker en arts. De academische literatuur in marketing laat een grote heterogeniteit zien in de schattingen van de effectiviteit van farmaceutische marketing. Verschillende verklaringen hiervoor zijn al gegeven, maar verrassend genoeg heeft tot nog toe niemand de rol van de inhoud van het artsenbezoek geanalyseerd. De hoofdvragen in dit onderzoek zijn: (1) Hoe reageren artsen op verschillende productkarakteristieken die besproken worden door de artsenbezoeker? (2) Bespreekt de artsenbezoeker voornamelijk de positieve informatie omtrent zijn product? (3) Zijn artsen meer of minder gevoelig voor positief gekleurde informatie over een product? Om dit te onderzoeken is een model nodig dat de effectiviteit van de marketing voor ieder artsenbezoek kan schatten en tegelijkertijd corrigeert voor de mogelijke endogeniteit van de allocatie van artsenbezoeken en de inhoud van het artsenbezoek. Hiervoor wordt een hiërarchisch Bayesiaans vector autoregressief (VAR) model gebruikt. Positief gekleurde informatie wordt daarin geoperationaliseerd door de inhoud van het artsenbezoek te linken met wetenschappelijke informatie over het medicijn.

De resultaten van deze analyse laten zien dat: (1) bedrijven bespreken de verschillende productkarakteristieken met de arts niet op hun optimale frequentie, (2) de inhoud van artsenbezoeken bevat positief gekleurde informatie omtrent het product en (3) het bespreken van positief gekleurde informatie werkt op de lange termijn negatief op de responsiviteit van de arts op het artsenbezoek. Dit alles suggereert dat bedrijven de inhoud van hun artsenbezoeken kunnen verbeteren en tegelijkertijd kan de aanpassing in het soort

informatie dat wordt besproken de zorgen van overheden wegnemen dat artsenbezoekers voornamelijk de positieve punten van een product bediscussiëren met de arts.

Het derde essay bestudeert de wisselwerking tussen het aantal voorgeschreven medicijnen, de marketinguitgaven voor die medicijnen en wetenschappelijke studies over die medicijnen. De farmaceutische industrie is een modelvoorbeeld van een industrie die op de wetenschap is gebaseerd. Producten in dit soort industrieën worden ondersteund door wetenschappelijke studies die voorafgaand en tijdens de levenscyclus van een medicijn verschijnen. De uitkomsten van die studies aangaande een bepaald medicijn zijn verschillend, zodat het totale wetenschappelijk bewijs voor een product over de tijd verandert. Dit essay onderzoekt daarom (1) hoe wetenschappelijke studies naar een product de marketing uitgaven van een bedrijf richting gebruikers van het product en experts beïnvloeden en (2) in welke mate beïnvloeden deze wetenschappelijke studies de verkopen van het product. Als een logische vervolgvraag daarop bestudeert het essay ook hoe het niet meenemen van wetenschappelijke studies in een model om de marketingeffectiviteit te meten de schattingen van de marketingeffectiviteit verandert.

Om deze vragen te beantwoorden wordt een uitgebreide dataset van wetenschappelijke studies naar producten binnen een belangrijke farmaceutische categorie gebruikt. Deze data worden gecombineerd met verkoopcijfers en marketinguitgaven voor de producten binnen de categorie. Om het dynamische effect van wetenschappelijke productstudies op verkopen en marketinguitgaven te meten, wordt een vector error correctie (VEC) model gebruikt. Drie maatstaven worden gebruikt om, op basis van de wetenschappelijke studies, alle informatie omtrent de kwaliteit van het product samen te vatten: de gemiddelde effectiviteit, de spreiding in de effectiviteit en het aantal studies dat verschenen is voor een product.

De resultaten laten zien dat alle drie de maatstaven een significante invloed hebben op de verkopen en de marketinguitgaven. Een hoger gemiddelde van de prestaties van een product leidt tot een stijging van de marketinguitgaven aan gebruikers en experts. Een hogere spreiding leidt tot een verschuiving van marketing aan gebruikers naar marketing aan experts. Een hoger aantal studies zorgt alleen voor een stijging in de marketinguitgaven richting experts. De verkopen van een medicijn worden positief beïnvloed door een hoger gemiddelde van de prestaties van het medicijn op basis van wetenschappelijke studies, alsmede het aantal studies. Ten slotte laat het onderzoek ook zien dat als de onderzoeker de invloed van wetenschappelijke studies over een product niet meeneemt in het model, zoals gewoonlijk gebeurt, er een te hoge schatting van het effect van marketing uit het model komt.

Elk essay bevat a substantiële component die relevant is voor managers en zodoende bevat het proefschrift belangrijke lessen voor zowel onderzoek als managers. Voor onderzoekers: (i) een nieuwe alternatieve methode is besproken om de gevolgen van een drastische beleidsverschuiving van een bedrijf te voorspellen, (ii) een model is uit de doeken gedaan om de effectiviteit van de inhoud van een artsenbezoek te meten en (iii) wetenschappelijke studies naar een product moeten worden meegenomen in een model om de effectiviteit van farmaceutische marketing te meten. Enkele lessen voor managers zijn als volgt: (i) de marktleider is in staat om de trend van het groeiende aantal artsenbezoekers te doorbreken, (ii) artsenbezoekers bespreken te vaak positief gekleurde informatie met de arts, hetgeen contraproductief is op de lange termijn en (iii) wetenschappelijke studies naar producten zijn een onderdeel van de marketingstrategie van een bedrijf en kunnen gebruikt worden om de strategie van de concurrent te voorspellen.

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Eelco Kappe was born in 1984 in ‘s-Gravenhage in The Netherlands. In 2006, he completed his master’s degree in econometrics (major quantitative marketing) cum laude at the Erasmus University Rotterdam and started as a Ph.D. candidate in the marketing department at the Erasmus School of Economics. His dissertation involves the study of pharmaceutical marketing effectiveness and combines the usage of cutting-edge econometric methods with unique data sources. His research is characterized by a strong managerial focus combined with rigorous empirical analyses.

He has presented his work at several international conferences, such as the marketing science conference in Singapore, Vancouver, Detroit and Cologne and the marketing dynamics conference in New York. He visited various doctoral consortia among which the AMA doctoral consortium at Georgia State University in Atlanta. He also worked a few months on his research at Quintiles and in fall 2009 he visited IESE Business School in Barcelona. The studies resulting from his dissertation are currently under review at Management Science, Marketing Science, and the Journal of Marketing.

Eelco continues his career in academia and in August 2011 he will start as an assistant professor at the marketing department of Pennsylvania State University. Besides his academic work, Eelco is an active sportsman and likes to travel.

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THE EFFECTIVENESS OF PHARMACEUTICAL MARKETING

Pharmaceutical marketing effectiveness comprises the measurement of marketing efforts of pharmaceutical firms towards doctors and patients. These firms spend billions of dollars yearly to promote their prescription drugs. This dissertation provides empirical analyses and methods to contribute to several substantial problems on pharmaceutical marketing effectiveness. Using unique data in every essay, it studies the role of the firm, sales rep and doctor in pharmaceutical marketing. The first essay evaluates the size of the sales force and the allocation of sales calls among doctors. In particular, it provides a method to gauge a yet-to-be-enacted firm-initiated policy shift. The second essay studies the effectiveness of the information content provided in sales calls. The main questions evolve around the discussion of positively biased drug information and the responsiveness of doctors to that. In the third essay, the interplay between drug sales, marketing and scientific reviews is studied in detail.

The essays reveal important implications for academics and managers. For academics: (i) a new alternative to gauge policy shifts is offered; (ii) a model is offered to analyze the effectiveness of sales message content; and (iii) scientific reviews should be considered to correctly measure pharmaceutical marketing effectiveness. The implications for managers are: (i) the market leader is able to buck the trend in increasing sales forces; (ii) sales reps discuss positively biased information too often, which is counterproductive in the long run; and (iii) scientific reviews on products should be actively considered as a part of the marketing mix.

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