PREDICTING THE CONSEQUENCES OF MARKETING POLICY CHANGES:

A NEW DATA ENRICHMENT METHOD WITH COMPETITIVE REACTIONS

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Abstract

We introduce a new data enrichment method that combines revealed data on consumer demand and competitive reactions with stated data on competitive reactions to yet-to-be-enacted, unprecedented marketing policy changes. We extend the data enrichment literature to include stated competitive reactions, collected from subject-matter experts through a conjoint experiment. We apply our method to investigate hypothetical and unprecedented salesforce policy changes of pharmaceutical companies. The results from our data enrichment method have high face validity and lead to various unique insights compared to using revealed data only. We find that only a very large salesforce decrease initiated by the market leader triggers all competitors to decrease their salesforce as well, leading to substantial profit increases for each firm. With respect to salesforce allocation, we find that when competitors decrease their salesforce they mainly decrease the reach of detailing across doctors, rather than decreasing the number of details to the most-visited doctors. Our data enrichment method provides managers with a powerful tool to ex ante predict the consequences of unprecedented salesforce and other marketing policy changes.

Keywords: Data enrichment, marketing policy, salesforce management, competitive reactions, conjoint analysis, pharmaceutical, detailing, prescriptions.

1 INTRODUCTION

Competitive reactions are an important part of firms' marketing strategies (e.g., Montgomery, Moore, and Urbany 2005; Soberman and Gatignon 2005; Steenkamp et al. 2005). It is through the lens of a competitive reactions framework that marketing managers learn whether or not they need to react to competitive actions (e.g., Carpenter et al. 1988; Leeflang and Wittink 2001). The competitive reactions framework has been used to understand when and how firms react to price promotion (e.g., Horváth et al. 2005; Leeflang and Wittink 1992; 1996), advertising (e.g., Steenkamp et al. 2005), and distribution decisions (e.g., Bronnenberg, Mahajan, and Vanhonacker 2000) of their competitors.

The competitive reactions framework has also been used to, *ex post*, assess the implications of unprecedented changes in competitors' marketing policies. Ailawadi, Lehmann, and Neslin (2001) study the impact of an unprecedented, sustained decrease in promotions and increase in advertising of Procter & Gamble. Chen, Sun, and Singh (2009) analyze the impact of a simultaneous 20% price increase of Philip Morris' low-tier brand and a 20% price decrease of its premium brand. Van Heerde, Gijsbrechts, and Pauwels (2015) study an unprecedented price war among supermarkets. In contrast, in this study we focus on, *ex ante*, assessing the implications of various unprecedented marketing policy changes. In other words, while prior literature has yielded valuable insights by assessing the impact of an unprecedented change in marketing policy after its occurrence, our aim is to introduce a data enrichment method by which managers can assess the impact of such changes before they are actually implemented.

An important consequence of studying unprecedented changes *ex ante* is that models solely estimated on revealed data may suffer from the Lucas (1976) critique, which states that one can provide only meaningful predictions using revealed data for situations that fall within the variation observed in the revealed data. To circumvent this problem, we develop a data enrichment method that enriches revealed data on past consumer demand and competitive reactions with stated data on competitive reactions to future unprecedented marketing policy changes. Our method contributes to the data enrichment literature, which has made major breakthroughs to enrich demand-side data (Feit, Beltramo, and Feinberg 2010; Sridhar, Bezawada, and Trivedi 2012; Swait and Andrews 2003). We are the first to extend the data enrichment method to investigate stated competitive reactions. More generally, our study contributes to a long tradition in marketing research of eliciting judgmental data from experts within the focal firm (e.g., Lodish et al. 1988; Rangaswamy, Sinha, and Zoltners 1990) as well as outside the focal firm (e.g., Gupta, Jain, and Sawhney 1999; Srinivasan, Park, and Chang 2005).

Substantively, we contribute to the competitive reactions literature by studying the consequences of various unprecedented salesforce changes in the pharmaceutical industry. Past research has yielded rich insights on competitive reactions to marketing-mix elements like price promotions and advertising. However, despite the importance of the sales function to firm growth (Zoltners, Sinha, and Lorimer 2009), competitive reactions to salesforce changes have received limited attention. Such issue is particularly relevant in the pharmaceutical industry to inform the ongoing policy debate questioning the ballooning size of its salesforces (Wall Street Journal 2013) and its influence on doctors (Mizik and Jacobson 2004).

In our empirical application, we enrich revealed data on doctor-level prescriptions and detailing with stated competitive reactions to various unprecedented detailing changes before they are initiated, collected from subject-matter experts through a conjoint experiment. As past literature has shown the importance of pharmaceutical salesforce size and allocation decisions, we collect stated competitive response data on both firm decisions (e.g., Manchanda, Rossi, and Chintagunta 2004; Zoltners, Sinha, and Lorimer 2006). We cooperated with Quintiles, a leading supplier of pharmaceutical salesforce services and consulting, and collected stated data from industry experts on six unprecedented salesforce-decrease scenarios in the statin category. The stated data is needed because the revealed detailing data for this category may suffer from the Lucas critique as it only contains limited variation with respect to the total salesforce size.

We compare our data enrichment method to two benchmark methods. First, we check the validity of some of our main findings by categorizing the competitive reactions to large salesforce decreases in a large number of other therapeutic categories. Based on aggregate-level detailing and prescriptions data from 2006-2012, we confirm that salesforce decreases by the market leader are more often followed by competitive decreases, compared to decreases initiated by market followers. This finding is in line with prior literature (Haveman 1993; Lieberman and Asaba 2006). However, we also document substantial heterogeneity in the response patterns across categories. Therefore, it is useful for managers to apply our data enrichment method for the specific category for which they consider unprecedented salesforce changes. Second, we compare our findings to those resulting from a model that only utilizes the revealed panel data for the statin category and ignores the stated data. The results for this benchmark model differ from those resulting from our data enrichment method and we argue that the findings from the data enrichment method are more in line with both the competitive reactions literature and the competitive reactions to large salesforce decreases in other categories.

Our empirical study yields several additional substantive insights. For instance, we find that only a large salesforce decrease of the market leader triggers all competitors to decrease their salesforce as well, leading to increased profits for all firms. Also, when firms decrease their detailing in response to competitive salesforce changes, they mainly decrease the reach of their detailing across doctors, rather than decreasing the number of details to the most-visited doctors.

Our findings have implications for pharmaceutical firms and policy makers, as we show that a large salesforce decrease of the market leader has the potential to decrease total detailing efforts within the category and increase profits for all firms involved. Methodologically, our data enrichment method offers a new tool to managers, which allows the inclusion of managerial judgment to predict the consequences of various alternative unprecedented marketing policy changes before they are initiated.

2 LITERATURE BACKGROUND

2.1 Competitive Reactions

Competitive reactions are an important part of firm strategy (e.g., Gatignon and Soberman 2002; Soberman and Gatignon 2005) and an important input factor to firms' marketing decisions (e.g., Dickson 1992; Montgomery, Moore, and Urbany 2005). Competition among firms is asymmetric (DeSarbo, Grewal, and Wind 2006) and competitive reactions are a function of three characteristics (Chen and Miller 2012): the attack, the attacker, and the defender. In this paper, we will use the more general words "salesforce change," "initiator," and "follower" to fit our application context. For instance, in our application, the reason for salesforce resizing may lie in cost reduction, rather than an attempt to increase market share.

Chen, Smith, and Grimm (1992) find that competitive reactions are significantly influenced by the intensity of the initiator's attack. Chen et al. (2002) find that attacks with a higher public commitment are more likely to be matched by defenders. Steenkamp et al. (2005) find that the strength of the defender's reaction increases with the market power of the attacker. Actions of larger and more successful attackers are also more likely to be mimicked by defenders (Haveman 1993; Lieberman and Asaba 2006). Defenders with higher market share are expected to react more quickly and intensely (Bowman and Gatignon 1995).

The present paper focuses on, ex ante, assessing consumer and competitive reactions to unprecedented marketing-mix changes, while prior work in this area studied reactions to such unprecedented changes ex post (Ailawadi, Kopalle, and Neslin 2005; Ailawadi, Lehmann, and Neslin 2001; Chen, Sun, and Singh 2009; Van Heerde, Gijsbrechts, and Pauwels 2015).

2.2 Data Enrichment

Data enrichment involves the collection of new data to complement existing data, improve inference, relax model assumptions, or answer new research questions not directly addressable using the revealed data only. The essential underpinning of data enrichment is that the stated and revealed data have at least some variables in common (Swait and Andrews 2003). Data enrichment differs from "data fusion," which takes the data "as it lies" (Feit et al. 2013).

The extant data enrichment literature combines revealed- and stated-preference data, either from the same individuals (Sridhar, Bezawada, and Trivedi 2012) or from different sets of individuals (Feit, Beltramo, and Feinberg 2010; Mark and Swait 2004; Swait and Andrews 2003). It combines the strengths of both data types: the high validity (based on actual decisions) of revealed-preference data and the good statistical properties (larger variation) of stated-preference data. The current study collects additional stated data on competitive reactions (i.e., reactions to salesforce changes).[1] We are the first to enrich data on firms' competitive reactions instead of consumers' behavior. Collecting stated data on competitive reactions raises additional challenges on the selection of respondents, which we address in Section 3.2.

We also add to prior studies that collect stated data on consumer and firm behavior. A good example is Gupta, Jain, and Sawhney (1999), who collect stated data from both consumers and software complementors and combine both datasets to simulate the digital television market

[1] We use the more general terms "revealed" and "stated data" in this paper, instead of revealed and stated-preference data, as the stated competitive reactions data we collect can technically not be considered preference data.

evolution. They do not integrate revealed data into their analysis. In contrast, we explicitly enrich revealed data on past consumer demand and competitive reactions with stated data on competitive reactions to various salesforce-change scenarios. Integration of revealed data allows us to exploit the benefits of the external validity of the revealed data and assess the validity of our stated data in a base scenario, designed to mimic the market situation in the revealed data.

3 OUR FRAMEWORK

We present our data enrichment framework for a yet-to-be-enacted, unprecedented salesforce change in a single marketing instrument. In our framework below, we assume that the consumer-demand parameters are stable before and after the salesforce change, but the competitive-reaction parameters are subject to change (see Section 8 for extensions to this framework, such as how to handle unstable consumer-demand parameters).

To predict the consequences of a salesforce change ex ante, we need three ingredients: (i) define the *salesforce-change scenarios*, i.e., a set of alternative initial actions of the salesforce-change initiator; (ii) *revealed* prescription and detailing *data* for the period before the salesforce change (i.e., the *base scenario*), which can be at the individual or aggregate level; in our case the data are at the individual level; (iii) collect *stated data* from experts on firms' competitive responses to the various salesforce-change scenarios (see Section 3.2).

3.1 Data Enrichment Steps

The data enrichment framework is shown in Figure 1 and consists of 6 steps:

[Insert Figure 1 about here]

Step 1: Estimate the consumer-demand and competitive-reaction models using the revealed data only (i.e., before the salesforce change).

Step 2: Estimate the competitive-reaction model for the base scenario on the stated data. Following the guidelines in Ben-Akiva et al. (1994) and Little (1970), the inclusion of a base scenario helps to test the validity of the stated data. The model based on the stated data should result in competitive-reaction parameters comparable to those from the revealed data (Feit, Beltramo, and Feinberg 2010; Mark and Swait 2004; Swait and Andrews 2003).

Step 3: Test for *base validity*. Test whether the competitive-reaction parameters under the base scenario for the revealed and stated data are similar using a statistical test, such as the Chow or likelihood-ratio test. Two outcomes are possible: (i) the parameters are similar and the base validity of the stated data is confirmed, and (ii) the parameters are different. In the latter case, one can apply a correction factor to scale the stated-data parameters to be equal to the revealed-data parameters. The choice of an appropriate scale factor depends on the cause for the difference and the specific model. For example, Mark and Swait (2004) find for a choice model that a subset of parameters has a different impact across the revealed and stated data and they apply a scale factor to the stated-data parameters to match the parameters in both data sources.

Step 4: Estimate the competitive-reaction model parameters for the salesforce-change scenarios in the stated data. This captures the competitive responses to the various salesforce changes not yet enacted in the revealed data. The estimation is done similarly as in Step 2. If Step 3 resulted in a scale factor, this factor should be used to scale the stated-data parameters.

Step 5: Predict the outcomes of the salesforce-change scenarios by combining the estimates on consumer demand, based on the revealed data obtained in Step 1, with the competitive-reaction model estimates for the salesforce-change scenarios obtained in Step 4 (including the application of a potential scale factor).

Step 6: Test for the internal validity of the predicted salesforce-change outcomes in step 5. For every scenario, split the stated data into an estimation and holdout sample (step 4). Predict the holdout sample based on the obtained parameters from the estimation sample in the same scenario. Compare the prediction accuracy on this holdout sample with predictions based on: (i) parameters for the other salesforce-change scenarios, and (ii) parameters for the revealed data only. These tests assess whether parameters based on the estimation sample from a specific scenario more reliably predict the holdout sample of that same scenario than parameters based on the other salesforce-change scenarios and the revealed data only.

Testing the accuracy of the predictions after the salesforce changes are enacted is not possible when one wants to *ex ante* predict the impact of multiple yet-to-be-enacted salesforce changes. Thus, it is important to clearly list the assumptions underlying each scenario to help firms understand the connection between the assumptions and the predictions resulting from the framework (this is similar to the approach taken in scenario planning, e.g., Schoemaker 1995).

3.2 Respondent Selection for Stated Data

Respondents who provide the stated data should be knowledgeable about the decisions at hand. Respondents are similar to key informants in that they should be able to provide reliable and valid data on how firms would respond to unprecedented salesforce changes (Homburg et al. 2012). First, this can be achieved by selecting respondents based on their experience with the decision tasks and industry under consideration (e.g., Best 1974; Rowe and Wright 1999) as individuals in higher hierarchical positions and with a longer tenure provide more reliable responses (Homburg et al. 2012). Second, we aggregate responses across multiple respondents to increase the reliability of the stated data (Homburg et al. 2012; Van Bruggen, Lilien, and Kacker 2002). Third, we carefully train respondents on the market situation and decision tasks to which they have to respond to maximize their knowledge of the context to reduce systematic response error (Lodish et al. 1988; Rangaswamy, Sinha, and Zoltners 1990). Fourth, we carefully word the decision tasks (e.g., no anchors, no ambiguity, and objective wording) to further reduce systematic error (Homburg et al. 2012; Podsakoff, MacKenzie, and Podsakoff 2012).

Finally, we caution against including respondents who currently work for competitors in the focal category as they may have an incentive to mislead the researcher. Using respondents from competitors may also lead to some legal risks as this may raise the suspicion of collusion among firms (Posner 2001). In our application, we have followed all the above guidelines.

4 DATA

In our data enrichment framework, we enrich revealed data on prescriptions and detailing with stated competitive-response data from a conjoint experiment. We discuss both datasets next.

4.1 Revealed Prescription and Detailing Data

We obtained in the statin category the discrete number of monthly self-reported total prescriptions (TRx), which includes new prescriptions and refill prescriptions, and detailing volume for a panel of 1,585 general practitioners in the United States, for the period August 2003 through May 2004. The panel, collected by a market research firm, is representative for the U.S. doctor population, both in terms of practice size and geography.

We focus on the four major statins in the market during our data period: Lipitor (Pfizer), Zocor (Merck), Pravachol (BMS), and Crestor (AstraZeneca). Crestor entered the market in August 2003 and was more effective than the incumbent drugs in decreasing low-density lipoproteins cholesterol, which is the primary benefit of statins. Table 1 summarizes the market share, detailing share, and the reach of detailing for each brand. Lipitor has the largest market share (50%) and Zocor and Lipitor have the highest share of detailing visits. It also shows the diversity in detailing strategies across brands. Lipitor reaches 78% of the doctors (i.e., 78% of the doctors receive at least one detailing visit during our data period), while Pravachol has a reach of only 46%. Zocor visits the doctors they reach more intensively, as they visit 20% of the doctors at least once a month. Web Appendix A, Table WA-A1, shows the correlations between prescriptions and detailing across all brands. In addition, the data only contain limited variation in the total number of detailing visits over time (see Web Appendix A for details). The only exception is Crestor, which shows a substantial increase in detailing during the data period as it just entered the market (Figure WA-A1). Table WA-A2 shows the monthly variation in detailing over time for each brand. At the monthly level, we occasionally observe a detailing decrease of more than 10% (once for Crestor and twice for Pravachol). However, for none of the brands we observe quarterly detailing decreases of more than 10% (strategic decisions about the size of the salesforce are typically made at the quarterly or the yearly level). We confirm this pattern using quarterly-level aggregate data on detailing expenditures for each brand.

[Insert Table 1 about here]

4.2 Stated Competitive-Response Data

We obtained stated competitive-response data from an online conjoint experiment in 2008/2009, in which experts were presented with a set of scenarios involving unprecedented downward detailing changes. We obtained a list of potential experts from Quintiles, a highly respected firm in the pharmaceutical industry. All potential respondents had worked in some way for or with Quintiles in the past, ensuring that they had a vested interest in providing truthful answers to Quintiles. We screened these potential experts by phone or email and asked them how much experience they had in making both salesforce allocation and size decisions in the U.S. prescription drug market. Experts indicating that they had over two years of experience in both salesforce allocation and size decisions, received a link to an online conjoint analysis.

From the people who passed our initial screening, 26 out of 63 experts participated in our conjoint experiment for a response rate of 41%. They included product/brand managers as well as directors and vice presidents of sales and marketing. Respondents worked for firms such as Abbott, Bayer, Eli Lilly, GSK, and Johnson & Johnson with, on average, over 10 years of experience in the pharmaceutical industry (19 out of 26 respondents had over 10 years of experience). We did not include respondents from firms active in the statin category, for reasons cited in Section 3.2. Our sample size is in line with the sample size used for the supply side in Gupta, Jain, and Sawhney (1999). In Section 6, we use a holdout sample analysis to show that our sample size is sufficient to make reliable predictions for each salesforce-change scenario.

We consistently informed respondents on the statin market around May 2004, such as manufacturer information, patent-protection time, and market shares (see Web Appendix B for details on the information we presented the respondents with). We also presented them pros and cons of hiring and firing sales reps. Next, we provided respondents with a *base scenario*, in which they were asked to take the position of one firm in the statin category and allocate detailing across four types of doctors. Based on the academic literature and discussions with pharmaceutical managers, we chose three attributes that determine the amount of detailing a doctor receives (Manchanda, Rossi, and Chintagunta 2004; Stremersch and Van Dyck 2009). The first attribute is the doctor's prescription volume, with levels: low (two prescriptions per quarter), middle (four prescriptions per quarter) and high (six prescriptions per quarter). The second is the doctor's responsiveness to detailing, whether low (the bottom tertile, the 33% of doctors least responsive to detailing), middle (the middle tertile) or high (the top tertile). The third is competitive detailing, with levels: low, middle and high, corresponding to one, three and five details per quarter (summed across competitors). The absolute values for the attribute levels for the doctor's prescription volume and competitive detailing are chosen to mimic the situation in the revealed data. For detailing responsiveness we chose only relative levels (low, middle, and high) as it is not intuitive to interpret the absolute values. We chose three levels for each attribute to allow for nonlinear effects and to not succumb to the number-of-levels problem (Wittink, Krishnamurthi, and Reibstein 1989). Given the limited number of doctor types that result (3^3 = 27), we created a full-factorial design and used an interchange heuristic to minimize the correlation between attributes within a respondent's profile.

Next, we presented respondents with three salesforce-change scenarios (referred to as policy shifts in the conjoint tasks) to assess their competitive reactions. Each scenario was unique along: (i) the size (reductions of 10%, 25%, and 40%), and (ii) the initiator (market leader, Lipitor; or market follower, Pravachol). This results in six possible scenarios from which three were randomly selected. We asked respondents to indicate the expected percentage change in the firm's salesforce size and to allocate their detailing across four doctor types in response to the salesforce change, compared to the base scenario. We repeated this three times in three different parts of the survey, totaling three base scenarios and nine salesforce-change scenarios. Within each part of the survey, the firm for which the respondents answered and the four doctor types among which they allocated detailing remained constant (see Web Appendix B for details). We checked the data for outliers and unrealistic response times, but found none. We collected data for each competitor in each salesforce-change scenario from at least ten unique respondents.

4.3 Enrichment Procedure

To compare the estimates resulting from the revealed and stated data (Step 2 of the framework), we needed to transform the stated data to a format similar to the revealed-data format. This transformation requires us to obtain for each scenario the detailing allocation across all doctors in our panel data. In the estimation, we can then replace the observed detailing allocation from the revealed data by the stated detailing allocation.

We obtained the stated detailing data by asking respondents to allocate 100 detailing visits over four different doctor types (the conjoint tasks). Such tasks are relatively simple and in line with respondents' daily decisions. For each conjoint task, we multiplied the stated allocation by the number of detailing visits these four doctor types jointly received in the last three months of the revealed data.[2] For every respondent, we then computed the average monthly number of detailing visits for each doctor type under the base scenario. For the salesforce-change scenarios, we adjusted the obtained number of detailing visits by the specified change in the salesforce size.

We obtain the number of detailing visits for all doctors in our panel by pooling for each scenario the obtained number of details across the conjoint respondents. Such aggregation of responses increases the reliability of the stated data (Homburg et al. 2012; Van Bruggen, Lilien, and Kacker 2002). We now have for each scenario and all 27 doctor types the stated number of details. As we have classified each of the 1,585 doctors in our data into one of the 27 doctor types, we can assign the stated number of details to the 1,585 doctors in our panel data, while making sure that we assign an integer number of details to each doctor.[3]

4.4 Descriptives

Table 2 reports the number of responses for each scenario, the mean and standard deviation of the detailing changes in the salesforce-change scenarios compared to the base scenario, and the percentage of respondents who changed the salesforce size. For example, the fifth row shows the reactions of Crestor to a 10% decrease in detailing of Lipitor. We have 13 responses, a mean detailing increase of 2.69% (st. dev. = 5.25), and 23.08% of respondents changed the salesforce size in response to Lipitor's detailing decrease.

[2] Under the *base scenario,* both datasets now have approximately the same number of average detailing visits.
[3] For example, if the average number of monthly detailing visits for a specific doctor type is .8, we randomly assign 80% of the doctors classified as that specific doctor type one detailing visit and zero for the remaining 20%.

[Insert Table 2 about here]

Table 2 leads to two insights on the changes in salesforce size. First, it makes a big difference whether Lipitor or Pravachol initiates an unprecedented salesforce change. While a detailing decrease for Lipitor triggers competitors to often decrease their detailing as well, a detailing decrease for Pravachol triggers competitors more often to increase their detailing. This finding is in line with Haveman (1993) and Lieberman and Asaba (2006), who find that the actions of the market leader (Lipitor) are more likely to be mimicked by competitors. An alternative explanation for this result is that Lipitor has a higher efficacy than Pravachol, but we cannot disentangle the effects of efficacy and market share in our application. Second, the scenario in which Lipitor decreases its salesforce by 40% is the only scenario in which all firms decrease their detailing efforts. Furthermore, on average, respondents changed the salesforce size in 33.76% of the salesforce-change scenarios compared to the base scenario. Our model-free evidence is in line with Chen et al. (2002) and Steenkamp et al. (2005), in that most competitive reactions are passive and that respondents change salesforce levels more often when the initiator has a higher market share and when the size of the change is bigger.

With respect to reallocation, Table 2 shows that, on average across scenarios, 52% of the respondents changed their salesforce allocation compared to the base scenario. This shows the importance of taking allocation into account compared to resizing only. Table 2 leads to two main insights. First, we observe a pattern in which larger salesforce changes induce more respondents to change their allocation. Second, respondents change the salesforce allocation for Pravachol less often compared to the other brands. As shown in Section 4.1, the detailing strategy of Pravachol is quite different from the other brands and the respondents in the stated data see less reason to change the allocation for Pravachol after a salesforce decrease of Lipitor.

Table 3 shows the revealed and stated detailing allocation under the base scenario after we assigned the stated data to the doctors in our panel (see Section 4.3). Table 3 shows, for each of the 27 doctor types and for each brand, the average number of monthly details based on both data sources. The last row of Table 3 shows the correlation between the revealed and stated data. The correlation is .70 or higher for Crestor, Lipitor, and Zocor, providing model-free assurance that our stated data have face validity. For Pravachol, the correlation is .49.

[Insert Table 3 about here]

5 MODEL

We use a two-step approach to model doctors' prescription behavior (consumer-demand model) and firms' detailing allocation (competitive-reaction model) on the revealed data. We first estimate unbiased and consistent consumer-demand parameters, following Manchanda, Rossi, and Chintagunta (2004), by correcting for the potential endogeneity of detailing.

The number of prescriptions is modeled as a multivariate Poisson regression model with a full covariance matrix, which allows for overdispersion (Chib and Winkelmann 2001). We extend Chib and Winkelmann's model by allowing for individual-specific parameters using a hierarchical Bayesian specification. The probability of l total prescriptions, TRx_{ijt}, for doctor i = 1…I, brand j = 1…J, in month t = 1…T is given by:

$$(1) \qquad \Pr\left(TRx_{ijt} = l \middle| \nu_{ijt}\right) = \frac{\exp(-\nu_{ijt})\nu_{ijt}{}^{l}}{l!},$$

$$(2) \qquad \nu_{ijt} = \exp\begin{bmatrix} \beta_{0ij} + \beta_{1ij}\ln\left(Det_{ijt}+1\right) + \sum_{k\neq j}\beta_{2ij}\ln(Det_{ikt}+1) + \\ \beta_{3ij}\ln\left(TRx_{ij,t-1}+1\right) + \sum_{k\neq j}\beta_{4ij}\ln\left(TRx_{ik,t-1}+1\right) + \\ \beta_{5ij}\ln(Trend_t) + \beta_{6ij}Trend_t + \beta_{7i}IntroCrestor_t + \xi_{ijt} \end{bmatrix},$$

$$(3) \qquad \beta_{ij} \sim MVN(\overline{\beta}_J, \Sigma_{\beta j}), \qquad \text{for } j = 1 \ldots J,$$

$$(4) \qquad \xi_{it} = \left\{\xi_{i1t} \ldots \xi_{iJt}\right\} \sim MVN\left(0_J, \Sigma_\xi\right).$$

Here, v is the conditional mean that has to be positive, as we only observe positive outcomes of TRx_{ijt}. Note that we add the value one to the variables for which we take the logarithm to ensure positivity. Det_{ijt} denotes the number of detailing visits during the corresponding time period.

β_{0ij} is a doctor and brand-specific constant capturing all time-invariant factors influencing the prescription behavior of doctor i for brand j. It reflects the doctor's base preference for a brand, but also subsumes other factors like the composition of the doctor's patient pool. The base prescription level of a doctor for a certain brand is likely to influence the detailing effort directed to that doctor by pharmaceutical firms (Manchanda, Rossi, and Chintagunta 2004).

β_{1ij} is doctor i's responsiveness to detailing for brand j, which is also likely to be correlated with the number of detailing visits for that doctor (Manchanda, Rossi, and Chintagunta 2004). β_{2ij} is a (J-1) vector measuring the effect of brand-specific competitive detailing on doctors' prescription behavior. β_{3ij} reflects the own-brand carryover effect for doctor i and brand j and the (J-1) vector β_{4ij} measures the carryover effects of competitive prescriptions.

β_{5ij} and β_{6ij} measure the doctor- and brand-specific effects of a time trend, capturing the dynamics caused by the introduction of Crestor, category expansion, and other unobserved news affecting the different brands. Both trend variables are scaled to lie between zero and one to improve the stability of the MCMC algorithm. We included a dummy *IntroCrestor*, taking the value one for Crestor in the first month of our data and zero for all other time periods and brands.

ξ proxies for other variables observed by the doctor, but not by the researcher. To capture the omission of unobserved variables, we include a full variance-covariance matrix Σ_ξ, which captures contemporaneous correlations between brands. The individual- and brand-specific β-parameters are multivariate normally (MVN) distributed (Equation 3), and $\Sigma_{\beta j}$ are full variance-covariance matrices to capture any dependencies across variables.

To correct for the strategic detailing behavior of firms, we follow Manchanda, Rossi, and Chintagunta (2004) and model the number of detailing visits by a Poisson model:

(5) $$\Pr\left(Det_{ijt} = m \middle| w_{ijt}\right) = \frac{\exp(-w_{ijt}) {w_{ijt}}^{m}}{m!},$$

(6) $$w_{ijt} = \exp\left[\gamma_{0j} + \gamma_{1j}\frac{\beta_{0ij}}{1-\beta_{3ij}} + \gamma_{2j}\frac{\beta_{1ij}}{1-\beta_{3ij}} + \gamma_{3j}\ln\left(\sum_{k\neq j} Det_{ik,t-1} + 1\right) + \zeta_{ijt}\right].$$

w_{ijt} is a function of the constant in the prescription equation β_{0ij}, the detailing response coefficient β_{1ij}, and competitive detailing. β_{0ij} and β_{1ij} are divided by $1\text{-}\beta_{3ij}$ to account for carryover effects. Note that both the prescription and detailing models include competitive activities. ζ has a normal distribution for brand $1 \ldots J$ and is uncorrelated with ξ in Equation 2. We estimate Equations 1-6 jointly, and the prescription and detailing model are related through the common appearance of β_{0ij}, β_{1ij} and β_{3ij}. In Web Appendix C, we discuss the full estimation procedure and the empirical identification of the model parameters.

Next, conditional on the estimation of the consumer-demand model and in line with Dong, Manchanda, and Chintagunta (2009), we estimate a competitive-reaction model on the revealed data based on the assumption that firms optimally allocate detailing.[4] This model allows us to interpret the detailing allocation in terms of marginal costs and marginal benefits. We use a two-step estimation approach for this structural competitive-reaction model in case we make incorrect assumptions on firms' supply-side behavior, which would then lead to inconsistent demand-side estimates (Chintagunta et al. 2006). Hence we sacrifice efficiency for consistency.

We assume that firms optimize a static objective function for every period and for every doctor. The objective function for doctor i, brand j, and month t is given by:

(7) $$\Pi_{ijt}\left(Det_{ijt}\right) = p_{jt}\mathrm{E}\left[TRx_{ijt}\right] - Det_{ijt}mcDet_{ijt} - fcDet_{jt}, \text{ for } t = 1 \ldots T,$$

[4] This assumption does not mean that firms cannot be better off after an unprecedented salesforce change. Instead, the assumption is similar to assuming locally optimal behavior (e.g., conditional on the size of the salesforce).

with Π_{ijt} representing the profits. We assume that the marginal costs of production are zero, such that the price, p_{jt}, is equal to the markup (as the marginal production costs are small, but unknown to the researcher). $mcDet_{ijt}$ is the marginal cost of detailing doctor i for brand j at time t, and $fcDet_{jt}$ is the fixed cost of detailing for brand j at time t. We assume that firms only have knowledge of the prescription model up to the error term, which we indicate by ν^*_{ijt} below, and hence we include the expected number of prescriptions in the objective function.

Under the assumption of a static Bertrand-Nash equilibrium, the optimal amount of detailing per doctor must satisfy the first-order condition:

$$\frac{\partial \Pi_{ijt}}{\partial Det_{ijt}} = 0,$$

which is equivalent to

$$p_{jt}\nu^*_{ijt}\frac{\beta_{1ij}}{Det_{ijt}+1} = mcDet_{ijt}. \tag{8}$$

To be able to combine the outcomes of the revealed prescription and detailing data with the collected stated competitive-response data, we make the marginal costs for every brand and scenario a function of the doctors' targeting attributes represented by dummy variables:

$$\begin{aligned} mcDet_{ijt} = \delta_{0j} + \delta_{1j}TRx\_Middle_{ij} + \delta_{2j}TRx\_High_{ij} + \delta_{3j}Resp\_Middle_{ij} + \\ \delta_{4j}Resp\_High_{ij} + \delta_{5j}CompDet\_Middle_{ij} + \delta_{6j}CompDet\_High_{ij} + \theta_{ijt}, \end{aligned} \tag{9}$$

with θ_{ijt} normally distributed. The base categories for each attribute are low prescription volume, low responsiveness, and low competitive detailing. These marginal-cost parameters reflect the effort for the sales rep to visit different types of doctors due to doctors' attitude toward detailing.

To estimate the competitive-reaction model on the stated data for the base scenario and the salesforce-change scenarios, we replace the observed detailing allocation in the revealed data by the stated detailing-allocation data (see Section 4.3). For each scenario, we can compute the marginal costs based on the left-hand side of Equation 8. p_{jt} is obtained from our data, Det_{ijt} is the detailing allocation based on the stated data, and ν^{*}_{ijt} and β_{1ij} are based on the estimates resulting from Equation 1-6. We estimate Equation 9 separately for each brand and scenario.

6 RESULTS

Step 1: Consumer-Demand and Competitive-Reaction Models on the Revealed Data

Table 4 shows the results of the consumer-demand and competitive-reaction models estimated on our revealed data. The MCMC sampler ran for 500,000 iterations, with the first 450,000 discarded for burn-in. We conclude that the MCMC sampler converged based on the convergence statistic of Gelman and Rubin (1992), which is below 1.1 for all parameters. The first row shows the brand constants, which are proportional to the brands' market shares. The (own) detailing effect is positive for all brands. Dividing the detailing effect by one minus the carryover effect, $\beta_{1ij} / (1-\beta_{3ij})$, we obtain the cumulative effects, which are: 1.73 for Crestor, .35 for Lipitor, .80 for Pravachol and .82 for Zocor. The detailing effect for Crestor is highest, which may be because it is the newest drug (Narayanan, Manchanda, and Chintagunta 2005) and/or because it is the most effective drug in the category (Venkataraman and Stremersch 2007).

[Insert Table 4 about here]

The competitive detailing effects of Lipitor and Zocor on Crestor are significantly negative, indicating that Crestor is the most vulnerable brand as doctors' preference structure is more uncertain for the new brand. In line with Dave (2013) and Stremersch, Landsman, and Venkataraman (2013), we find a mix of negative and positive competitive detailing effects. The carryover effects are positive for all brands, largest for Crestor (.51) and smallest for Lipitor (.21). The competitive carryover effects of prescriptions are small, ranging from -.10 to .06.

For Crestor, we observe a positive, marginally decreasing trend over time. For Lipitor, the trend coefficients are small, and Pravachol and Zocor have a negative trend. This pattern fits the maturity of the drugs in the category. We estimate a negative introduction dummy for Crestor of -.30. We also find significantly positive covariance between all brands. The results of the covariance matrices $\Sigma_{\beta j}$ can be found in Web Appendix D, Table WA-D1 through WA-D4.

The results for Equations 5 and 6 to correct for detailing endogeneity are shown at the bottom of Table 4. We find that prescription volume positively affects the number of detailing visits. The effect is significant for all brands, except Pravachol (.03), and largest for Crestor (.90). The effect of doctors' responsiveness to detailing on the number of details is significantly positive for all brands. Manchanda, Rossi, and Chintagunta (2004) found a negative effect for this variable and attributed this to the absence of competitive detailing in their dataset. We verify their assertion that with the inclusion of competitive detailing, the response parameter of detailing responsiveness is positive. The competitive detailing parameters can be interpreted as elasticities and we find that detailing significantly increases with the number of competitive detailing visits (cf. Chan, Narasimhan, and Xie 2013; Dong, Chintagunta, and Manchanda 2011). These results suggest that firms mimic each other's detailing strategies.

We performed several robustness checks on the model discussed above. We compared various operationalizations based on the deviance information criterion (DIC). The DIC for our main model is 160,226.81. Following Dong, Manchanda, and Chintagunta (2009), we operationalized detailing in Equation 2 by $1 / (1 + Det_{ijt})$, which led to a DIC of 160,457.52. We tested different trend terms, such as only a linear trend (DIC = 160,658.98). Following Horváth et al. (2005), we tested for the presence of own-brand and cross-brand feedback effects in Equation 6, but we found that the large majority of these effects is insignificant.

Table 5 shows the marginal-cost parameters based on Equation 9. As we use effects coding for the estimation[5], the constant reflects the average marginal cost of a detailing visit, ranging from $106 for Crestor to $164 for Lipitor. These marginal costs are in line with the empirical estimates of Dong, Manchanda, and Chintagunta (2009) and Liu et al. (2016).

[Insert Table 5 about here]

Across all brands, the marginal cost of visiting a doctor with a low prescription volume is substantially lower than for a doctor with a high prescription volume. Doctors who are highly responsive to detailing have a lower marginal cost, and this effect is significant for all brands. This can be explained by the easier access to these doctors. Finally, for Lipitor and Zocor, the marginal cost of visiting a doctor increases in the number of competitive detailing visits. Overall these effects indicate that marginal costs are driven by the ease of access to the doctor's office.

Step 2: Competitive-Reaction Model for Base Scenario on the Stated Data

Table 6 shows the results for the marginal-cost parameters based on the stated data. The signs of the majority of parameters are similar to the ones resulting from the revealed data. However, standard deviations are bigger, most likely as a result of our limited sample size.

[Insert Table 6 about here]

Step 3: Test for Base Validity

Section 4.4 provides model-free evidence that our stated data have face validity. Now, we test whether the data-generating process for detailing is common to both our stated and revealed data. For the base scenario, we conduct a Chow test, on a brand-by-brand basis, to test the similarity of the marginal-cost parameters resulting from Equation 9 based on the revealed and

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[5] Effects coding implies that the parameters for the levels within an attribute sum to zero. Therefore, the effect of the reference category for each attribute is not included in the constant and the brand constants approximate the average marginal cost of detailing.

stated data. The critical value for the Chow test with seven parameters is 2.01, based on α of .05. The test statistic for the different brands is: Crestor (1.07), Lipitor (1.87), Pravachol (1.18), and Zocor (1.63), which shows that we cannot reject the null hypothesis of equal parameters resulting from both data sources. Hence, we show the base validity of our stated data and its ability to track marginal costs akin to having these recovered from revealed data alone.[6]

Step 4: Competitive-Reaction Model for Salesforce-Change Scenarios on the Stated Data

Applying the same procedure as in the base scenario (see Section 4.3), we calculate the detailing allocation across all brands and doctors under the various salesforce-change scenarios. We assume that the prescription model parameters are invariant to the salesforce change. There are several reasons why we think this is a valid assumption. First, we observe sufficient variation in the number of detailing visits across doctors. Specifically, we consider multiple salesforce-decrease scenarios, while our data contains, at the individual doctor-level, a lot of zeros for the number of detailing visits, which inform the parameters in our hierarchical Bayesian consumer-demand model. Second, we only consider a change in detailing within a single therapeutic category, while doctors receive detailing visits for drugs in hundreds of therapeutic categories. There is no reason to expect that a detailing decrease in a single category will affect the overall responsiveness of doctors to detailing as such.

This assumption allows us to predict the resulting number of prescriptions for each doctor under the various salesforce-change scenarios in the stated data. The consumer-demand parameters and stated detailing levels can be used to estimate marginal-cost parameters for every salesforce-change scenario. As this estimation gives many different parameters, we do not show

[6] We also tested for pooling using a likelihood-ratio test when using the number of detailing visits (instead of the marginal costs) as the dependent variable. We found that parameters for three brands could be pooled, but for a fourth brand a scale factor was necessary.

these regression outcomes. Results show that the marginal-cost parameters differ substantially across scenarios, though the uncertainty is also relatively large. We observe a pattern that average marginal costs decrease with the salesforce size, indicating economies of scale.

Step 5: Outcomes for the Salesforce-Change Scenarios

To predict the outcomes of the salesforce-change scenarios, we combine the prescription-model estimates based on the revealed data with the competitive-reaction model estimates for the various salesforce-change scenarios. We use the estimates for the salesforce-change scenarios (Equation 9) to optimally allocate the detailing across the 1,585 doctors in our panel data, while ensuring that each doctor gets assigned an integer number of details. Table 7 shows for each of the six scenarios the relative differences between the situation before and after the salesforce change, computed by *(new value – old value) / old value*. The results show, respectively, the relative changes in details, prescriptions, market share, profits, and market size. As an example, the first row considers the consequences for Crestor after a 10% detailing decrease of Lipitor. This scenario leads to a relative salesforce increase for Crestor of 2.77%, a 6.20% increase in prescriptions, a 5.81% increase in market share, a 10.82% increase in profits, and a market size increase of .36%.[7] All these outcomes, except the market size change, are significantly different from zero based on 1,000 Monte Carlo simulations. We calculated profits based on the costs of a detailing visit and the revenues of prescriptions. We assume a cost of $150 for an average detailing visit (all-in, except samples), based on company records of Quintiles. This number is also in line with empirical estimates in Dong, Manchanda, and Chintagunta (2009) and Liu et al. (2016). However, multiple drugs may be discussed during a detailing visit. Based on an independent panel dataset from IMS Health, we found that the average number of drugs

[7] Note the small discrepancy between the detailing changes in Table 2 and Table 7. The reason is that respondents in our stated data only allocated detailing across four randomly selected doctor types, instead of all 27 doctor types.

discussed in a detailing visit between 2002 and 2008 is 1.31, leading to an average cost of discussing a single drug during a detailing visit of $115 (= $150 / 1.31).[8] We assume revenues of a single prescription of $70 for Crestor, $90 for Lipitor, $80 for Pravachol, and $100 for Zocor.[9]

[Insert Table 7 about here]

Table 7 leads to the following conclusions. First, in line with the descriptive findings in Section 4.4, a detailing decrease for market-leader Lipitor triggers competitors to often decrease their detailing as well, while a decrease in detailing for Pravachol triggers competitors more often to increase their detailing.

Second, looking at each brand's optimal allocation across scenarios (not explicitly shown here) shows that a detailing decrease in response to a large salesforce change leads to a decreased reach of detailing compared to the situation before the salesforce change in Table 1. After a salesforce decrease, sales reps for Crestor, Lipitor, and Zocor (not for Pravachol) focus more intensively on the doctors with lower marginal costs. The results show that a detailing decrease is mainly caused by a decrease in detailing visits to the doctors that already receive little attention.

Third, based on our cost and revenue assumptions, all scenarios in which Lipitor decreases its salesforce are beneficial to all firms, though not always significantly so. Table 7 shows the largest profit increases when Lipitor decreases detailing by 40%, which is the only scenario in which all competitors also significantly decrease their detailing. In this scenario, relative profits significantly increase for Crestor (34.05%), Lipitor (6.40%), Pravachol (4.43%), and Zocor (2.33%). We have also calculated for this scenario how much of the gain comes from resizing and reallocation. Ignoring the reallocation data (i.e., we only use the data on salesforce

[8] Alternatively, we can directly use the estimated marginal costs for each doctor type under each scenario. We have done this in a robustness check, which led to comparable results.
[9] IMS Midas price system and "Consumer Reports Best Buy Drugs: The Statin Drugs" (January 2006).

size), average profits across brands are 17% lower. This implies that 83% of the profit increases in this scenario comes from resizing the salesforce and the remaining 17% is due to reallocation.

Fourth, for every salesforce-change scenario, the initiator increases its profits. Profits of competitors either increase or decrease. For example, Lipitor's profits decrease after a 10% and 40% salesforce decrease of Pravachol, but increase after a 25% salesforce decrease of Pravachol.

We ran a sensitivity analysis for the most profitable scenario in which Lipitor decreases its salesforce by 40%. We calculated the relative profit changes under a low ($100) and high ($150) estimate for the detailing costs and a low (25% lower) and high (25% higher) revenue per prescription. Table 8 shows that the outcomes are quite robust to the chosen numbers.

[Insert Table 8 about here]

Step 6: Validation

We assess the internal validity of our predictions using a holdout sample. This is also a test on whether our sample size for the stated data is big enough to make reliable inferences on the different salesforce-change scenarios. We randomly select the holdout sample, which consists of 35% of the respondents' answers. This allows us to predict the detailing allocation in the holdout sample using the remaining 65% (estimation sample) of observations. We re-estimate the marginal-cost parameters for each scenario using the estimation sample. Using the resulting marginal-cost parameters, we compute the optimal allocation across doctors, assuming a static Bertrand-Nash equilibrium between firms. We compare this allocation with the allocation in the holdout sample and compute the root mean squared prediction error (RMSPE). We also compute the RMSPE for every scenario using: (i) the allocation based on the stated data for the other salesforce-change scenarios, and (ii) the allocation based on the revealed data only.

Table 9 shows the results. The first column shows that using the marginal-cost estimates based on the 25% salesforce-decrease scenario of Lipitor, the RMSPE is 145% of the RMSPE using the estimation sample from the 10% salesforce decrease of Lipitor. It also shows that neither any of the other scenarios nor the revealed data predict the holdout sample better than the estimation sample of the scenario under consideration. Overall, Table 9 shows that, for four out of six scenarios, the predictions on the holdout sample are best using their own estimation sample. For the remaining two scenarios the predictions based on their own estimation sample are second best. We conclude that the stated data collected from multiple experts is consistent within each scenario and consistently different across scenarios.

[Insert Table 9 about here]

7 BENCHMARKING

As our data enrichment method requires the collection of additional stated data, we assess the gains from collecting this additional data and the added model complexity by comparing our method to two benchmark methods.

7.1 Revealed Data on Salesforce Decreases in a Large Number of Other Categories

We assess whether data from other therapeutic categories that have witnessed large salesforce decreases is informative on the consequences of the unprecedented changes we consider in the statin category. We use quarterly, brand-level data on detailing expenditures and prescription revenues from 2006-2012. To match the scenarios in our stated data, we define three salesforce-decrease categories: (i) decreases from 10-17.5% (representing the 10% salesforce-decrease scenario); (ii) decreases from 17.5-32.5% (representing the 25% salesforce-decrease scenario); (iii) decreases of more than 32.5% (representing the 40% salesforce-decrease scenario). We separately assess firms' competitive reactions to salesforce decreases initiated by the market leader and the market follower. Web Appendix E shows the results (Table WA-E1) and describes the assumptions we made on which salesforce decreases to include in our analysis. In summary, we find that a large salesforce decrease of the market leader leads substantially more often to a decrease in the salesforce of the competitors as well, compared to when a market follower initiates the decrease. So, the general patterns from this analysis are in line with our stated data. However, we still observe quite some variation in the competitive responses across therapeutic markets and brands, which supports a more in-depth analysis for a specific therapeutic category. We conclude that the additional data collection and model complexity for our data enrichment method allows more specific predictions on the consequences of large salesforce decreases within a single therapeutic category, compared to this benchmark.

7.2 Revealed Data Only for the Focal Category

We also assess the gains that our data enrichment method brings by collecting additional stated data, as compared to using revealed data only. The main downside of only using revealed data is that it contains limited variation in monthly salesforce changes. We only observe three instances in which the salesforce decreases by more than 10%, with a maximum decrease of 13.32%. Hence, the usage of revealed data variation only may suffer from the Lucas critique when predicting larger salesforce decreases (i.e., a model estimated on revealed data only may provide accurate predictions for salesforce decreases up to 10%, but its predictions for 25% and 40% decreases may be increasingly inaccurate as predictions stretch further away from the variation observed in the data). To examine whether this is the case, we compare the predictions of our data enrichment method on revealed and stated data with a benchmark model on revealed data only. Web Appendix E contains the detailed specification and estimates of this benchmark model, in which we allow for firm-specific competitive reactions and for competitive reaction elasticities that vary nonlinearly based on the aggregate-level salesforce changes of competitors. Next, we summarize the findings on this benchmark model.

First, for the 10% salesforce-decrease scenarios, we find that only one out of six predictions for detailing by our data enrichment method on revealed and stated data significantly differs from the predictions of the benchmark model on revealed data only. Thus, for predictions within the bounds of the revealed data, the data enrichment method on revealed and stated data adds little insight, but rather confirms the results from a revealed data only model.

Second, for larger salesforce decreases the predictions are increasingly different. For the 25% salesforce-decrease scenario we find four out of six predictions for detailing by our data enrichment method on revealed and stated data to significantly differ from the predictions of the benchmark model on revealed data only. For the 40% salesforce-decrease scenario we find five out of six predictions for detailing to be significantly different across both methods. An important reason for these differences is the limited variation in the aggregate-level salesforce changes in the revealed data, which has a big impact when extrapolating (i.e., predicting the 25% and 40% salesforce-decrease scenarios) outside the variation in the revealed data.

Third, we examine these differences in more detail to assess which method produces the predictions with the highest face validity. We find that the predictions from the data enrichment method on revealed and stated data are consistent with both the competitive reactions literature and our empirical inquiry on other therapeutic categories (Section 7.1). The predictions from the benchmark model using only revealed data run counter to both prior literature and the findings on other therapeutic categories. An important prediction of our data enrichment method is that salesforce decreases of 25% and 40% initiated by the market leader are more likely followed by competitors than when initiated by the market follower. Such finding aligns both with prior studies by Chen et al. (2002) and Lieberman and Asaba (2006) and the findings in Section 7.1. In contrast, our benchmark model on revealed data only, predicts that salesforce decreases of 25% and 40% initiated by the market follower are equally likely followed by competitors as similarly-sized salesforce decreases by the market leader. We conclude that the predictions from our data enrichment method have higher face validity than those from the benchmark model on revealed data only, showing the value of our data enrichment method over using revealed data only.

8 EXTENSIONS

Below, we discuss we discuss some extensions to our data enrichment method. First, if one's goal is to examine unprecedented salesforce changes on the size of the salesforce and leave the allocation across consumers stable, one can simplify our framework. In this case, there is no need for individual-level demand data, and aggregate-level sales models can be used to model demand (e.g., time-series models). One can simplify the competitive-reaction model (Equations 5-9) to reflect how firms react to each other's budget decisions at the market level, and include some smaller budget changes in the stated data to assess the base validity.

Second, our data enrichment framework may be used to study changes in areas other than sales, such as advertising or price. For example, studying unprecedented price changes requires the researcher to model firms' pricing decisions (i.e., update the competitive-reaction models in our framework along the lines of Horváth and Fok 2013 or Sudhir 2001). An unprecedented price change often involves multiple products per firm. In this case, one may have to include (competitive) cross-price effects in the competitive-reaction model. The base scenario would then focus on small price changes and the unprecedented scenarios would study large changes.

Third, to study scenarios involving multiple marketing instruments, one should design more extensive scenarios involving decisions on several instruments at the same time (e.g., akin to the value-pricing policy shift of P&G). The researcher needs to specify a competitive-reaction model for each marketing instrument, which are potentially interrelated. For example, we could ask respondents for their responses to scenarios in which the initiator substantially decreases the salesforce, but increases medical journal advertising.

Fourth, we have assumed stable consumer-demand parameters. However, if consumer-demand parameters are expected to change, one can also collect stated data from consumers. For example, when a new product is introduced, one can use conjoint analysis to collect preference data from consumers (Mark and Swait 2004). This extension bears similarities to the approach of Gupta, Jain, and Sawhney (1999). However, within our framework, the revealed data are still necessary to establish the validity of the stated data in a base scenario and, if necessary, provide guidance to the researcher on how to adjust the parameters based on the stated data.

9 IMPLICATIONS AND FUTURE RESEARCH

In this paper, we provide a data enrichment method to predict the consequences of yet-to-be-enacted, unprecedented marketing policy changes. Our method enriches revealed data on consumer-demand and competitive reactions with stated data on competitive reactions to the yet-to-be-enacted, unprecedented marketing policy changes. We collected the stated data from experts through a conjoint experiment. Methodologically, we extend the data enrichment literature by being the first to use data enrichment to investigate competitive reactions (which brings its own challenges in the selection of respondents). Substantively, we extend the competitive reactions literature by, ex ante, predicting the consequences of unprecedented marketing policy changes, while prior literature does so only ex post. Managers can use our method to predict the consequences of unprecedented marketing policy changes motivated by reasons internal (e.g., financial difficulties) or external (e.g., big macroeconomic changes) to the firm, or if they feel that the market they operate in is in a suboptimal situation. Our method allows the inclusion of managerial judgments, which has been shown to increase the adoption of the model recommendations (e.g., Lilien and Rangaswamy 2008; Wierenga, Van Bruggen, and Staelin 1999). Moreover, our method helps firms to enlighten the mechanisms underlying the consequences of an unprecedented marketing policy change, which can enable fruitful discussion in a management team as to the likelihood of the outcome also occurring in reality.

Our empirical findings offer several important managerial insights. While a salesforce decrease of market-leader Lipitor triggers competitors to decrease their salesforce as well, a decrease of Pravachol triggers competitors to increase their salesforce more often. Given our cost assumptions, all salesforce-change scenarios for the market leader are profitable for all firms involved. Only a large salesforce decrease of 40% of market-leader Lipitor leads all competitors to decrease their salesforce as well, making this the most profitable scenario. These findings may be relevant to firms and policy makers concerned with the intensive salesforce efforts in the pharmaceutical industry. With regards to detailing allocation, a salesforce reduction primarily leads to a decrease in detailing to doctors that were already getting few visits. This decreased reach of detailing may be helpful for smaller brands, which get increased opportunities to visit doctors that do not receive any competitive detailing visits.

Predicting the consequences of yet-to-be-enacted, unprecedented marketing-mix changes is a challenging problem, and hence we have set some boundaries in our empirical application. First, we focused on single-market competition, but pharmaceutical firms compete with each other in multiple markets (Kang, Bayus, and Balasubramanian 2010). For tractability, we also restrict our analysis to competitive reactions using the same marketing instrument (which is the most common situation; e.g., Steenkamp et al. 2005), though we discuss how to extend our framework to consider multiple marketing instruments. It would also be interesting to apply our method to salesforce-increase scenarios as we only focused on salesforce-decrease scenarios.

Second, we study a firm's decision on one brand in isolation, while a firm's salesforce size and allocation decisions may show interdependencies across brands in the firm's portfolio. Sales reps may also discuss multiple drugs during a detailing visit. We leave it to future research to extend our framework to the impact of imminent salesforce changes across a firm's product portfolio. In any case, it is important to educate expert respondents about any important strategic considerations of the firms in the market, such that they can take these into account when providing their responses (something we have not explicitly done in the current study).

Third, we consider the salesforce change of the initiator as fixed (i.e., the initiator does not react to competitive reactions following its initiation). In reality, a large marketing-mix change may involve multiple rounds of competitive reactions. For example, the Dutch retail price war (Van Heerde, Gijsbrechts, and Pauwels 2015) took multiple rounds. Though, the price-policy shift of Philip Morris (Chen, Sun, and Singh 2009) involved only one round. Extending our research to multiple-round interactions between firms seems valuable.

Fourth, we only consider competitive reactions to salesforce-change scenarios for four drugs. Hence, we cannot distinguish to what extent our results are driven by the characteristics of each drug (e.g., relative drug efficacy). Future research could investigate how drug characteristics may moderate the competitive reactions to unprecedented salesforce changes.

Fifth, a limitation of our current study is that the stated data has been collected about five years after the situation observed in the revealed data. While we have carefully briefed the respondents about the market situation in the revealed data, this still provides the risk of respondents ignoring some strategic considerations of firms specific to the time period of the revealed data in their stated decision making.

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TABLES AND FIGURES

Table 1: Descriptives for the Revealed Data

Drug	Market Share	Detailing Share	Detailing Reach	Detailing Reach at least Once a Month
Crestor	8%	25%	62%	14%
Lipitor	50%	31%	78%	18%
Pravachol	14%	12%	46%	5%
Zocor	29%	31%	71%	20%

Table 2: Number of Responses for Each Scenario in the Stated Data and the Changes in Detailing for the Salesforce-Change Scenarios

Drug	Scenario	Total Responses	Mean Change in Detailing	St. Dev. of Change in Detailing	% of Respondents Changing the Salesforce Size
Crestor	Base Scenario	20	-	-	-
Lipitor	Base Scenario	19	-	-	-
Pravachol	Base Scenario	20	-	-	-
Zocor	Base Scenario	19	-	-	-
Crestor	- 10% Lipitor	13	2.69%	5.25	23.08%
Pravachol	- 10% Lipitor	15	-.20%	2.51	13.33%
Zocor	- 10% Lipitor	11	-3.64%	5.52	36.36%
Crestor	- 25% Lipitor	12	1.15%	6.18	38.46%
Pravachol	- 25% Lipitor	14	-1.07%	2.89	14.29%
Zocor	- 25% Lipitor	13	-6.92%	10.11	38.46%
Crestor	- 40% Lipitor	12	-10.00%	14.14	58.33%
Pravachol	- 40% Lipitor	13	-9.62%	12.98	46.15%
Zocor	- 40% Lipitor	13	-17.69%	20.37	76.92%
Crestor	- 10% Pravachol	15	.00%	.00	.00%
Lipitor	- 10% Pravachol	15	3.33%	12.91	6.67%
Zocor	- 10% Pravachol	15	-5.33%	20.66	6.67%
Crestor	- 25% Pravachol	11	19.09%	24.98	45.45%
Lipitor	- 25% Pravachol	13	-5.77%	9.76	30.77%
Zocor	- 25% Pravachol	11	6.36%	12.86	27.27%
Crestor	- 40% Pravachol	12	18.75%	21.44	50.00%
Lipitor	- 40% Pravachol	14	3.46%	8.26	53.85%
Zocor	- 40% Pravachol	12	4.17%	10.19	66.67%
Average across all responses and scenarios					33.76%

Table 3: Comparison of the Revealed and Stated Detailing Allocation under the Base Scenario

				Average Number of Monthly Details Based on Revealed Data				Average Number of Monthly Details Based on Stated Data			
Doctor Type	**Prescription Volume**	**Respon-siveness**	**Competitive Detailing**	**Crestor**	**Lipitor**	**Pravachol**	**Zocor**	**Crestor**	**Lipitor**	**Pravachol**	**Zocor**
1	Low	Low	Low	.02	.05	.01	.02	.04	.06	.01	.01
2	Middle	Low	Low	.01	.04	.02	.04	.04	.03	.01	.10
3	High	Low	Low	.29	.34	.03	.10	.31	.30	.03	.09
4	Low	Middle	Low	.01	.08	.01	.02	.07	.03	.03	.02
5	Middle	Middle	Low	.02	.06	.01	.03	.13	.03	.07	.04
6	High	Middle	Low	.50	.26	.01	.11	.15	.36	.03	.34
7	Low	High	Low	.05	.26	.08	.34	.18	.02	.18	.06
8	Middle	High	Low	.13	.43	.06	.26	.13	.21	.16	.44
9	High	High	Low	.61	.52	.09	.26	.45	.27	.07	.54
10	Low	Low	Middle	.04	.03	.02	.04	.03	.00	.05	.04
11	Middle	Low	Middle	.03	.04	.03	.01	.03	.12	.03	.19
12	High	Low	Middle	.27	.24	.03	.24	.17	.33	.00	.28
13	Low	Middle	Middle	.02	.02	.03	.05	.02	.04	.04	.05
14	Middle	Middle	Middle	.02	.03	.01	.10	.07	.37	.13	.06
15	High	Middle	Middle	.43	.23	.03	.28	.29	.58	.21	.47
16	Low	High	Middle	.11	.08	.09	.29	.02	.05	.04	.11
17	Middle	High	Middle	.18	.41	.08	.34	.05	.27	.24	.36
18	High	High	Middle	.61	.61	.08	.36	.39	.67	.33	.55
19	Low	Low	High	.01	.15	.19	.23	.06	.18	.01	.06
20	Middle	Low	High	.03	.10	.16	.23	.31	.06	.06	.28
21	High	Low	High	.33	.46	.26	.29	.53	.68	.15	.51
22	Low	Middle	High	.01	.11	.14	.33	.25	.22	.11	.04
23	Middle	Middle	High	.08	.14	.15	.43	.30	.55	.07	.33
24	High	Middle	High	.39	.52	.16	.38	.42	.57	.16	.57
25	Low	High	High	.18	.37	.22	.48	.27	.35	.22	.45
26	Middle	High	High	.22	.26	.29	.61	.23	.35	.18	.43
27	High	High	High	.67	.67	.32	.63	.76	.56	.32	.72
	Correlation with Revealed Data							.75	.70	.49	.70

Table 4: Parameter Estimates for Prescriptions and Detailing Model Based on the Revealed Data

Prescription Model	Crestor	Lipitor	Pravachol	Zocor
Constant	**-3.65**	**.56**	**-.83**	**-.14**
	(-3.87,-3.48)	(.50,.62)	(-.94,-.76)	(-.22,-.07)
Detailing	**.85**	**.28**	**.51**	**.61**
	(.79,.95)	(.24,.32)	(.42,.62)	(.55, .65)
Carryover Effect	**.51**	**.21**	**.36**	**.26**
	(.48,.55)	(.19,.23)	(.33,.41)	(.23,.29)
TRx Crestor (t-1)		.00	-.02	.03
		(-.03,.03)	(-.07,.02)	(-.01,.08)
TRx Lipitor (t-1)	-.01		-.02	-.00
	(-.09,.07)		(-.07,.01)	(-.03,.04)
TRx Pravachol (t-1)	**-.10**	-.01		-.03
	(-.18,-.04)	(-.04,.02)		(-.07,.01)
TRx Zocor (t-1)	.03	.00	**.06**	
	(-.03,.09)	(-.03,.03)	(.02,.13)	
Detailing Crestor		-.00	-.01	-.00
		(-.04,.04)	(-.06,.03)	(-.05,.03)
Detailing Lipitor	**-.35**		**-.15**	**-.06**
	(-.46,-.27)		(-.22,-.08)	(-.10,-.01)
Detailing Pravachol	.01	**.10**		.03
	(-.10,.09)	(.04,.18)		(-.02,.09)
Detailing Zocor	**-.14**	**.08**	**.07**	
	(-.22,-.08)	(.03,.10)	(.00,.15)	
Trend	**2.83**	-.05	**-.18**	**-.21**
	(2.47,3.25)	(-.09,.02)	(-.23,-.07)	(-.30,-.12)
Exp(Trend)	**-.79**	**.08**	**-.29**	.05
	(-1.06,-.53)	(.04,.14)	(-.33,-.24)	(-.02,.18)
Intro Crestor	**-.30**			
	(-.52,-.09)			
Covariance				
Crestor	**.15**	**.04**	**.04**	**.05**
	(.11,.18)	(.03,.06)	(.02,.06)	(.04,.07)
Lipitor	**.04**	**.08**	**.07**	**.06**
	(.03,.06)	(.07,.09)	(.06,.08)	(.06,.07)
Pravachol	**.04**	**.07**	**.12**	**.07**
	(.02,.06)	(.06,.08)	(.10,.14)	(.06,.08)
Zocor	**.05**	**.06**	**.07**	**.09**
	(.04,.07)	(.06,.07)	(.06,.08)	(.08,.10)
Detailing Model				
Constant	-.04	**-1.81**	**-.90**	**-1.68**
	(-.25,.29)	(-2.06,-1.59)	(-1,15, -.67)	(-1.93, -1.47)
TRx Volume	**.90**	**.54**	.03	**.28**
	(.75,1.03)	(.40,.68)	(-.17, .29)	(.07, .50)
Responsiveness	**.73**	**.98**	**.72**	**.51**
	(.46,.97)	(.74,1.30)	(.48, .95)	(.16, .87)
Competitive Detailing (t-1)	**.14**	**.14**	**.32**	**.19**
	(.09,.19)	(.10,.19)	(.27,.40)	(.16,.23)

* The 2.5th and 97.5th percentiles are given in parentheses. Values in bold are significant.

Table 5: Estimates of the Marginal Costs under the Base Scenario Based on the Revealed Data

		Revealed Data			
		Crestor	**Lipitor**	**Pravachol**	**Zocor**
	Constant	**105.54**	**164.31**	**128.73**	**110.32**
		(86.65, 120.20)	(149.64, 179.48)	(107.91, 151.01)	(92.97, 129.69)
Prescription Volume	Low	**-10.68**	**-28.99**	**-18.08**	**-27.73**
		(-16.70, -4.57)	(-36.24, -20.02)	(-26.00, -7.90)	(-36.17, -18.40)
	Middle	3.14	-.99	3.38	-3.37
		(-5.48, 12.88)	(-6.76, 4.57)	(-4.61, 9.43)	(-12.87, 6.64)
	High	**7.54**	**29.99**	**14.71**	**31.10**
		(.51, 14.99)	(23.25, 36.58)	(8.11, 20.72)	(22.89, 39.44)
Responsive-ness to Detailing	Low	**12.18**	**9.92**	3.60	**12.33**
		(3.83, 20.85)	(2.03, 17.41)	(-4.76, 13.99)	(2.92, 22.64)
	Middle	4.61	4.32	**14.15**	-1.70
		(-4.04, 12.73)	(-3.18, 11.76)	(6.03, 22.29)	(-10.45, 6.05)
	High	**-16.80**	**-14.23**	**-17.75**	**-10.63**
		(-25.12, -8.26)	(-21.43, -7.12)	(-26.37, -8.22)	(-18.10, -1.99)
Competitive Detailing	Low	-.96	**-12.64**	-5.26	**-17.52**
		(-10.51, 9.24)	(-22.47, -4.68)	(-10.58, 1.59)	(-27.57, -6.58)
	Middle	-.68	-4.34	2.48	5.86
		(-8.75, 7.64)	(-13.24, 4.54)	(-3.04, 9.60)	(-3.32, 15.54)
	High	1.64	**16.98**	2.78	**11.66**
		(-7.88, 9.42)	(8.22, 25.87)	(-5.09, 9.62)	(3.81, 19.11)

Note: The results are estimated using effects coding.
* The 2.5th and 97.5th percentiles are given in parentheses. Values in bold are significant.

Table 6: Estimates of the Marginal Costs under the Base Scenario Based on the Stated Data

		Stated Data			
		Crestor	**Lipitor**	**Pravachol**	**Zocor**
	Constant	**112.16**	**186.24**	**132.20**	**137.63**
		(88.56, 133.86)	(164.11, 209.32)	(109.18, 154.61)	(112.61, 165.16)
Prescription Volume	Low	-12.63	**-37.99**	**-14.73**	**-29.71**
		(-25.94, 1.32)	(-51.82, -23.51)	(-26.76, -1.92)	(-46.71, -12.11)
	Middle	2.76	-10.03	3.84	6.59
		(-12.87, 19.79)	(-25.80, 4.83)	(-8.49, 16.70)	(-8.21, 21.07)
	High	9.87	**48.03**	10.89	**23.12**
		(-4.21, 24.98)	(30.11, 64.55)	(-2.33, 23.65)	(7.87, 38.11)
Responsive-ness to Detailing	Low	7.99	-9.76	7.41	**19.49**
		(-5.72, 22.92)	(-23.54, 3.74)	(-7.40, 22.46)	(2.03, 38.18)
	Middle	6.47	8.37	8.88	5.74
		(-8.84, 22.06)	(-3.18, 11.76)	(-5.44, 24.51)	(-11.68, 25.53)
	High	**-14.46**	1.39	**-16.29**	**-25.23**
		(-28.11, -.87)	(-9.22, 12.57)	(-30.10, -2.98)	(-44.27, -7.03)
Competitive Detailing	Low	.19	-11.45	-1.01	-13.47
		(-11.68, 12.65)	(-25.95, 3.46)	(-13.15, 11.02)	(-33.37, 6.69)
	Middle	.03	**-14.13**	7.04	5.41
		(-12.84, 12.93)	(-25.85, -.83)	(-6.44, 21.57)	(-13.45, 22.2)
	High	-.21	**25.57**	-6.03	8.06
		(-12.17, 11.95)	(12.84, 37.04)	(-18.81, 7.07)	(-13.01, 27.75)

Note: The results are estimated using effects coding.
* The 2.5th and 97.5th percentiles are given in parentheses. Values in bold are significant.

Table 7: Outcome Measures after the Salesforce Changes

Change in Detailing	Change Initiator	Brand	Details	Prescriptions	Market Share	Profits	Market Size
		Relative Market Changes after the Salesforce Change					
-10%	Lipitor	Crestor	2.77%*	6.20%*	5.81%*	10.82%*	.36%
		Lipitor	-10.00%*	-.55%*	-.91%*	1.63%*	
		Pravachol	-.24%	.56%	.20%	.89%	
		Zocor	-3.65%*	-.69%	-1.05%	.55%	
-25%	Lipitor	Crestor	1.02%	7.02%*	6.96%*	22.76%*	.06%
		Lipitor	-25.00%*	-1.36%*	-1.42%*	4.10%*	
		Pravachol	-1.02%	1.36%	1.30%	2.33%*	
		Zocor	-6.75%*	-1.20%	-1.26%	1.13%	
-40%	Lipitor	Crestor	-9.12%*	-2.83%*	-.58%	34.05%*	-2.26%*
		Lipitor	-40.00%*	-2.31%*	-.04%	6.40%*	
		Pravachol	-8.87%*	.58%	2.91%*	4.43%*	
		Zocor	-16.95%*	-3.38%*	-1.14%*	2.33%*	
-10%	Pravachol	Crestor	-.76%	-1.27%	-.45%	-1.26%	-.82%
		Lipitor	3.92%	.10%	.93%	-.78%	
		Pravachol	-10.00%*	-2.21%*	-1.41%*	.96%	
		Zocor	-5.87%	-1.45%	-.63%	.41%	
-25%	Pravachol	Crestor	16.68%*	22.95%*	20.07%*	8.17%*	-2.39%*
		Lipitor	-5.33%*	-.32%	-2.65%*	.84%	
		Pravachol	-25.00%*	-4.09%*	-6.34%*	4.42%*	
		Zocor	6.09%	1.40%*	-.97%	-.57%	
-40%	Pravachol	Crestor	18.58%*	23.90%*	21.51%*	2.50%*	1.97%*
		Lipitor	3.65%	.00%	-1.93%	-.84%	
		Pravachol	-40.00%*	-7.72%*	-9.51%*	5.42%*	
		Zocor	4.13%	.76%	-1.18%	-.66%	

* The 95% confidence interval does not contain zero based on a 1,000 Monte Carlo simulations taking into account the uncertainty in the consumer-demand and competitive-reaction parameters.

Note: The differences for details, prescriptions, market share, profits, and market size are relative differences, computed by (new outcome – old outcome)/(old outcome).

Table 8: The Main Results Are Stable to Changes in Detail Costs and Revenues per Prescription

Scenario	Brand	Change in Relative Profits after the Salesforce Change			
		Revenues -25% Detail costs 100	**Revenues -25% Detail costs 200**	**Revenues +25% Detail costs 100**	**Revenues +25% Detail costs 200**
Lipitor -40%	Crestor	23.04%*	14.46%*	39.71%*	29.62%*
	Lipitor	8.17%*	15.95%*	3.35%*	6.87%*
	Pravachol	5.35%*	10.15%*	2.96%*	4.67%*
	Zocor	3.71%*	11.02%*	.14%	2.69%*

* The 95% confidence interval does not contain zero based on a 1,000 Monte Carlo simulations taking into account the uncertainty in the consumer-demand and competitive-reaction parameters.

Note: The relative increase in profits for Crestor in the third scenario is very large due to the small absolute profits before the salesforce change.

Table 9: RMSPE Shows Consistency of Predictions within the Scenarios

		RMSPE for the Holdout Sample of this Scenario					
		10% Lipitor	**25% Lipitor**	**40% Lipitor**	**10% Pravachol**	**25% Pravachol**	**40% Pravachol**
Estimation sample based on data from the following scenario	10% Lipitor	–	123%	398%	136%	181%	171%
	25% Lipitor	145%	–	241%	291%	189%	283%
	40% Lipitor	372%	212%	–	367%	509%	487%
	10% Pravachol	114%	187%	355%	–	226%	177%
	25% Pravachol	167%	233%	488%	159%	–	118%
	40% Pravachol	182%	218%	376%	152%	97%	–
	Revealed data	108%	142%	342%	96%	142%	161%

Note: The RMSPE is calculated as a percentage of the RMSPE of the to-be-predicted scenario (i.e., an RMSPE above 100% indicates that the predictions have a higher RMSPE than the predictions using the estimation sample of the to-be-predicted scenario).

Figure 1: Data Enrichment Framework