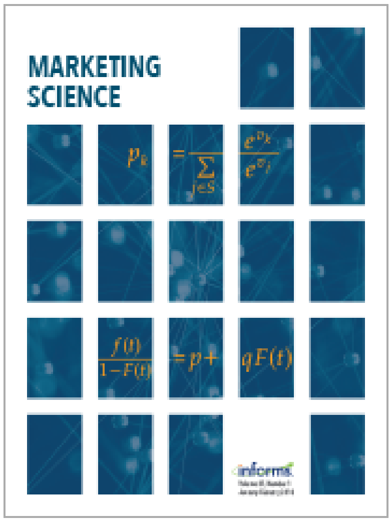


Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

The Cross Attributes Flexible Substitution Logit: Uncovering Category Expansion and Share Impacts of Marketing Instruments

Qiang Liu, Thomas J. Steenburgh, Sachin Gupta

MARKETING SCIENCE
Vol. 34, No. 1, January–February 2015, pp. 144–159
ISSN 0732-2399 (print) | ISSN 1526-548X (online)

http://dx.doi.org/10.1287/mksc.2014.0886

The Cross Attributes Flexible Substitution Logit: Uncovering Category Expansion and Share Impacts of Marketing Instruments

Qiang Liu
Krannert School of Management, Purdue University, West Lafayette, Indiana 47907, liu6@purdue.edu

Thomas J. Steenburgh
Darden School of Business, University of Virginia, Charlottesville, Virginia 22904, steenburght@darden.virginia.edu

Sachin Gupta
Samuel Curtis Johnson Graduate School of Management, Cornell University, Ithaca, New York 14853, sg248@cornell.edu

Different objectives such as category demand expansion or market share stealing warrant the use of different marketing instruments. To help brand managers make informed decisions, it is essential that marketing mix models appropriately measure their effects. Random Utility Models that have been applied to this problem might not be adequate because they do not allow the effects of marketing instruments of one brand to spillover to preference for competing alternatives. Additionally, they have the Invariant Proportion of Substitution (IPS) property, which in some situations imposes counter-intuitive restrictions on individual choice behavior. Recognizing that effects of marketing instruments can spill across brands in a category, we propose an alternative choice model that relaxes the IPS property: the cross attributes flexible substitution logit model. We apply the model in two very different empirical settings, i.e., consumer choices of brands of refrigerated yogurt, and prescription-writing choices of physicians in the hyperlipidemia category. In both settings the proposed model provides consistent evidence that certain marketing instruments produce sales gains primarily from growing the category pie, while others produce gains from stealing share. By contrast, the random coefficient logit and generalized nested logit models both predict that gains from all marketing instruments would have similar sources.

Keywords: brand switching; choice models; econometrics; logit; marketing mix effects; category expansion; invariant proportion of substitution
History: Received: September 2, 2011; accepted: August 22, 2014; Preyas Desai served as the editor-in-chief and Gary Russell served as associate editor for this article. Published online in *Articles in Advance* November 24, 2014.

1. Introduction

Brand managers carefully build their marketing portfolios to meet the sales and market share goals of the brand. Available marketing instruments differ by industry and change over time, but typically include pricing, advertising, trade promotions, consumer promotions, in-store merchandising, and professional selling, as well as longer-term choices such as product-line depth and breadth. Because marketing instruments influence consumer behavior in different ways, brand managers use a variety of marketing instruments, each with different strengths, to achieve the right mix. For instance, in the early stages of the product life cycle, brand managers may emphasize advertisements that build and promote category awareness. In the later, more mature stages of the life cycle, they may emphasize promotions that steal market share from competing firms.

Some marketing investments are more effective in growing category demand, others in stealing share from competitors. For example, the "Got Milk" campaign was clearly intended to grow primary demand for the category, i.e., milk. Similarly, campaigns that encourage the use of a brand in situations typically associated with other categories are intended to draw new buyers into the category. For example, Kellogg's created an advertising campaign to encourage consumers to eat Special K breakfast cereal instead of cookies in the afternoon (Wansink 1994). Unilever created a campaign for Lifebuoy in emerging markets to encourage hand washing with soap that has produced sales gains mainly by bringing new users into the category. These types of campaigns might even benefit other brands in the market. By contrast, the "Pepsi Challenge" clearly was intended to steal market share away from Coke. Similarly, temporary reductions in the price of a brand on the retail shelf typically have a brand switching goal. Nijs et al. (2001) reports that such price promotions rarely have persistent category expanding effects, while new product introductions do expand the category.

Consequently, some marketing actions are more threatening to competitors than others. At one extreme, actions that attract new buyers into the market or find new uses for existing products grow category demand and may be welcomed by competing firms. On the other hand, actions that primarily induce buyers to switch from competing brands in the category hurt competing brands' sales and share. Accordingly, a brand manager may expect different degrees of competitive retaliation to different marketing instruments; an instrument that inflicts greater damage on a competing brand is more likely to elicit a hostile reaction.[1]

To help brand managers make informed investment decisions, it is essential that marketing mix models accurately measure the different effects of marketing instruments. Although discrete choice models have been used in the past to analyze how consumers respond to various marketing actions (Bucklin et al. 1998, Bell et al. 1999), recent work suggests that extant models may be less than ideal to study this problem. Classical Random Utility Models (RUMs) such as the multinomial logit (MNL), nested logit (NL) (Ben-Akiva 1973), Generalized Nested Logit (GNL) (Wen and Koppelman 2001), and probit models do not allow the effects of marketing instruments for one brand to spillover to competing brands. Furthermore, they make it appear that all marketing instruments are identical in terms of the source of share gains because they have the Invariant Proportion of Substitution (IPS) property (Steenburgh 2008). A central argument of this paper is that the IPS property implies an overly restrictive set of consumer substitution patterns. We show that this property can misguide managers as to where the additional demand has originated.

To address this problem, we propose the Cross Attributes Flexible Substitution Logit (CAFSL) model, which relaxes the IPS property and more accurately measures how consumers respond to different marketing instruments. In a simulation experiment in which the sources of demand vary significantly across marketing instruments, we demonstrate that even after allowing for unobserved heterogeneity via random coefficient (RC) specifications, the MNL and GNL do a poor job of estimating the extent of sales gains due to brand switching versus category expansion.

We then provide empirical demonstrations in two very different contexts in which these issues are of central concern. The first context is consumer choice among alternative brands of refrigerated yogurt and the no-purchase option, a setting in which retailer feature advertising, TV advertising, and prices influence choices. We find that the effects of advertising and price spillover to competing brands, with resulting implications for category expansion versus brand switching effects of these two instruments. By contrast, the effects of retailer feature advertising do not spillover. The second context is physicians' prescription choices of drugs for treating hyperlipidemia. We find that patient-directed marketing instruments such as Direct to Consumer Advertising (DTCA) often work quite differently in terms of sources of demand gains than physician-directed marketing actions such as detailing. These results have important implications for brand managers in the case of pharmaceutical markets, and also for public policy makers.

In both empirical settings we find that the two extant models that suffer from the IPS restriction lead to counterintuitive estimates of the sources of demand gains due to increased investments in different marketing instruments. For instance, in the yogurt application, both the RC logit and the RC GNL models overestimate the percentage of share drawn from competing brands due to increased TV advertising (40.1% and 52.3%, respectively, versus 2.1% in CAFSL) and the percentage of share drawn from the no-purchase option due to lower prices (53.1% and 45%, respectively, versus 0.8% in CAFSL). Our results suggest that competing brands should be threatened much less by increased TV advertising than by price cuts.

The rest of this paper is organized as follows. In §2 we discuss the theoretical roots of the IPS property and propose the CAFSL model. In §3 we describe the data. In §4 we discuss results of our empirical analysis. Section 5 provides concluding remarks and suggestions for future research.

2. Model

To begin, we discuss RUM and the IPS restrictions. We then propose a model that allows for greater flexibility in substitution patterns across marketing instruments. We also discuss the extant models that serve as benchmarks and the flexibility that taste heterogeneity adds to these models.

[1] Some empirical evidence shows that managers' competitive reactions do take consumer response into account. Leeflang and Wittink (2001) find empirically that the greater the cross-brand demand elasticity, the greater the competitive reaction elasticity. Steenkamp et al. (2005) find that competitors' response to price promotions is considerably stronger than competitors' response to advertising. This is consistent with the conventional wisdom that sales gains from advertising are derived more from category expansion than from price promotions. Considerations of likely competitive response naturally affect the manager's choice of the optimal marketing mix.

2.1. RUM Models and the Invariant Proportion of Substitution (IPS) Property

The MNL model belongs to a broad class of RUM models that are the standard in the field today. As is well known, the restrictive error structure of the MNL model imposes Independence from Irrelevant Alternatives (IIA), an undesirable assumption about how decision makers substitute among alternatives, on individual and aggregate choice behavior. Many alternative RUM models with more general error structures, such as the NL, GNL, and the RC logit, have been proposed to overcome this deficiency and allow more realistic choice behavior to be predicted.

Although less frequently discussed in the literature, RUM models are based on other assumptions that impose restrictions on individuals' preferences and choice behavior. One such assumption is that an individual's preference between any two alternatives does not depend on the composition of the choice set. This implies that an individual's preference between any two alternatives, (e.g., A and B), cannot depend on the attributes of a competing alternative C. RUM models impose this restriction by assuming that the indirect utility function for alternative j depends only on its own attributes x_j, such that

$$v_j = v_j(x_j). \tag{1}$$

Thus, changing the attributes or price of alternative j will affect an individual's preference for it relative to all competing alternatives. Yet, it will not affect the individual's preference between any two other competing alternatives.[2]

An example will help to clarify this point. Suppose a market consists of three alternatives: the no-purchase option is alternative 0, Yoplait is alternative 1, and Dannon is alternative 2. The indirect utility functions are

$$v_0 = 0,$$
$$v_1(x_1) = -1 + 0.5 \cdot x_1,$$
$$v_2(x_2) = -2 + 0.5 \cdot x_2,$$

where $x_1 = 1$ is the advertising level of Yoplait and $x_2 = 2$ is the advertising level of Dannon. If Dannon increases its advertising, e.g., from 2 to 5, Dannon becomes more attractive relative to both Yoplait and the outside option. Yet Dannon's advertising increase does not affect the relative preference between Yoplait and the outside option because v_0 and v_1 do not change.

[2] The partial derivative of the indirect utility for alternative k with respect to attribute a (or price) of alternative j is zero: $\partial v_k/\partial x_{ja} = \partial v_k/\partial p_j = 0 \ \forall k \neq j$. Therefore, the relative preferences of any two competing goods, e.g., k and l, remain the same no matter what changes are made to good j.

This assumption is intuitively appealing in many situations, though not all. For instance, it is widely argued that marketing promotions have the potential to spill over to competing products in the same category. Advertising intended to increase consumer awareness of the advertised product might also remind consumers of nonadvertised competing options. Persuasive information provided by certain promotions of a particular product may convince consumers that all products in the category have some superior characteristics, and consequently, boost the utility of all products in the category. Using data from randomized field experiments Sahni (2013) analyzes the impact of online advertising by a restaurant and finds significant positive causal effects on sales leads for competing, nonadvertised restaurants. In the auto industry, Kwoka (1993) has documented a market-wide effect of firms' advertising. Thus, if a promotion has strong spillover effects, it may lead to category expansion that benefits competitors as well, thereby dampening cross-brand substitution.

Other types of promotions may have negative spillover effects on competing brands. For instance, negative comparative advertising by a brand is often intended to convince consumers that competing brands have inferior characteristics, and therefore, to decrease the utility of those goods (Just et al. 2004). A very large fraction of advertising in political campaigns is negative, and this fraction is larger in close races (Lovett and Shachar 2011). Batra and Homer (2004) explore the conditions in which negative political advertising successfully damages voter attitudes towards the targeted candidate. Furthermore, research indicates that negative campaign advertising turns voters off and keeps people away from the polls, thus shrinking the market (Ansolabehere and Iyengar 1997). In the over-the-counter (OTC) drug market, comparative advertising has been found to damage competing brands (Anderson et al. 2012, Liaukonyte 2012).

Turning next to the possibility of spillover effects due to prices, considerable literature has supported the idea that consumers compare the actual prices of a product against a reference price in the process of making purchasing decisions (Winer 1986, Kalwani et al. 1990). Two alternative conceptualizations of how reference price is formed are based on past prices (temporal) and contemporaneous prices of other products in the category (contextual). A contextual reference price (Rajendran and Tellis 1994) would imply that the effect of a particular product's price extends to the attractiveness of competing products.

Two ideas become clear from examination of these prior studies. First, the possibility of spillover effects suggests that we might consider a broader range of indirect utility functions. Specifically, we might consider the possibility that marketing actions affect not only the preference for the promoted brand relative to all other possibilities but also that they may affect the relative preference between other competing brands. For example, when Dannon advertises it might affect not only the preference of Dannon relative to all goods in the market, but it might also increase preferences for other yogurts, such as Yoplait, relative to the no-purchase option. This suggests that the utility function of each yogurt should include not only its own attributes but also the attributes of competing alternatives, such that

$$v_j = v_j(x_1, \dots, x_J), \tag{2}$$

where v_j denotes the indirect utility and x_j denotes a vector of attributes for good j.

Returning to the previous example, we can show one possible way that spillover might be modeled. The following set of indirect utility functions allow advertising to (1) increase the preference for a brand relative to all goods in the market, and (2) increase the preference for yogurt relative to the outside option.

$$\begin{aligned} v_0 &= 0, \\ v_1(x_1, x_2) &= -1 + 0.5 \cdot x_1 + 0.1(x_1 + x_2), \\ v_2(x_1, x_2) &= -2 + 0.5 \cdot x_2 + 0.1(x_1 + x_2). \end{aligned}$$

Unlike the standard conceptualization, Dannon's advertising affects an individual's preference for Yoplait relative to the no purchase option through the overall advertising level, $x_1 + x_2$.

As Koppelman and Sethi (2000) point out, specifying an indirect utility function that includes the attributes of competing alternatives is rarely done in the literature, perhaps due to the related issues that the model may produce counter-intuitive elasticities (Ben-Akiva 1974), and that it may not satisfy the RUM principles. Note that these potential objections have not been thoroughly discussed in the literature, which explains why we believe they are not limiting in our case.

The idea that specifying an indirect utility function that includes the attributes of competing alternatives produces counter-intuitive elasticities stems from Ben-Akiva (1974, p. 4), who argues that "Applying this procedure results in some cross-elasticities having the wrong sign." Specifically, Ben-Akiva's argument is based on the premise that own-price elasticities should be negative and cross-price elasticities should be positive. Ben-Akiva shows that specifying an indirect utility function that includes the attributes of competing alternatives implies that some of the cross-price elasticities can be negative and therefore concludes that this specification produces counter-intuitive elasticities. We point out that Ben-Akiva actually makes a claim only about *price* elasticities. We are not aware of other arguments that have been made suggesting that the elasticities are more generally counter-intuitive.

Given this, we believe that a compelling argument can be made in our case to allow for a broader specification. To begin with, Ben-Akiva's argument pertains solely to price elasticities and does not take into account the possibility of spillover in other marketing instruments. While it may be reasonable to assume that the own-advertising elasticity must be positive, there is no reason to believe that the cross-elasticity of advertising must be negative. In fact, the possibility of advertising spillover means that the elasticity might take a positive sign, too. So the basic premise of Ben-Akiva's argument does not apply to nonprice marketing instruments. Furthermore, even when it comes to price, an argument can be made that the cross-price elasticities could be negative. Reference-pricing effects open the door to this possibility, and it seems reasonable to empirically test for this possibility rather than to assume that it cannot occur.

A related concern, which also has not (to our knowledge) been thoroughly discussed, is that specifying an indirect utility function that includes the attributes of competing alternatives might not satisfy the necessary RUM conditions. We will provide an example to explain why this may happen and argue that spillover makes it reasonable to allow non-RUM behavior. As discussed in McFadden (1981), Marschak (1960) and Block and Marschak (1960) established regularity as a necessary condition of RUM. Under regularity, the probability of choosing an alternative cannot increase if a new alternative is added to the choice set. In our example, this means the probability of choosing Yoplait cannot increase if Dannon were added to the choice set. The concept of spillover, however, suggests that this condition may not hold. If Dannon runs a big advertising campaign on entry, it might benefit other yogurt brands, too, making Yoplait and other brands more attractive relative to the outside option. Note that the regularity condition rules this out as a possibility. Therefore, we argue that it is reasonable to specify a model that allows for non-RUM behavior and to empirically test whether it occurs in the data.

Second, note that previous empirical studies suggest that marketing instruments may differ in their impact on an individual's preferences. Some marketing instruments have positive spillover effects, which mean that consumers might become more likely to buy yogurt, even if it is not the advertised brand, rather than nothing at all. Other campaigns have negative spillover effects, which means consumers become more likely to buy nothing at all rather than a brand of yogurt. Standard discrete choice models, however, have another property that limits their ability to detect this possibility.

Steenburgh (2008) shows that a broad class of choice models have the IPS property. Formally, IPS means that the proportion of demand drawn from a given competing good is the same no matter which attribute is improved.

$$\frac{\partial P_k/\partial x_{ja}}{\partial P_j/\partial x_{ja}} = C \quad \forall a,$$

where C is a constant and P_j is the probability that an individual chooses alternative j.

IPS is a restriction *imposed* by the demand model that may be too strong in some situations. In our example, IPS would imply that the proportion of demand drawn from the outside option would be the same, regardless of whether Dannon conducted a "Got Yogurt" advertising campaign or in-store, blind taste tests against Yoplait. Instead, it seems reasonable to hypothesize that a greater proportion of demand would be drawn from the outside option if Dannon conducted a "Got Yogurt" campaign than if it conducted a taste test against Yoplait. Ultimately, it is an empirical question as to whether marketing instruments have different impacts on individual choice behavior.

While the IIA property has been widely discussed in the literature, IPS has been discovered only recently, and little has been written about it. Therefore, we want to be clear that while some similarities exist between the properties, they are not identical and cannot be addressed in the same way. In fact, Steenburgh (2008) shows that many of the models that have been proposed to address issues stemming from IIA do not address issues stemming from IPS. For example, generalized extreme value models, including the NL and GNL models, and the covariance probit model all have the IPS property and the restrictive substitution patterns it implies.

The choice model we propose in this paper relaxes the IPS property and allows individual choice behavior to vary across marketing instruments. We do this by specifying an indirect utility function that depends on the attributes of competing goods, one of the basic assumptions that leads to the IPS property (Steenburgh 2008, p. 303). In essence, our proposed model allows us to kill two birds with one stone: (1) it allows the possibility that effects of marketing actions can spill over to other goods, and (2) it allows the substitution ratios to vary across marketing instruments.

2.2. Cross Attributes Flexible Substitution Logit Model

We build our proposed model on the well known NL model. Consider the choice decision of a consumer facing a market with J alternatives. Let the choice set be grouped into N nonoverlapping nests denoted by $B_1, B_2, \ldots, B_N$. Let x_j be (nonprice) promotion of alternative j, $j \in B_n$, whose effects may spill over to other alternatives within the nest. In addition to βx_j, the direct effect of x_j on the decision maker's indirect utility for alternative j typically seen in RUM models, we introduce an additional term $\gamma(\sum_{l\in B_n} x_l)$. In this specification, the summation of promotions for alternatives in nest n, $\sum_{l\in B_n} x_l$ accounts for possible spillover effects and acts as a nest-level attribute. This formulation implies that an increase in x_j affects the decision maker's utilities as follows: (i) It increases preference for alternative j over competing alternatives in the same nest by β; (ii) It increases preference for alternative j over alternatives outside the nest by $\beta+\gamma$; (iii) It increases preference for each alternative in the same nest as j, other than j, over alternatives outside the nest, by γ. The inclusion of the term $\gamma(\sum_{l\in B_n} x_l)$ in the model specification gives us a general framework for empirical work. If γ is zero, it indicates that the spillover effect is zero, while a non-zero γ indicates that the focal marketing instrument affects consumers' utility for all brands in the nest.

Next, we set up a general form of the indirect utility function to capture the possible price spillover discussed previously. Following Rajendran and Tellis (1994), we use the mean price of alternatives in nest n, p_n, as the contextual reference price. We can now write the indirect utility for alternative j in nest n as

$$v_j = \alpha_j + \beta x_j + \gamma\left(\sum_{l\in B_n} x_l\right) + \omega\xi_1 p_j + (1-\omega)\xi_2(p_j - p_n),$$

where the total price effect is a weighted average of the brand's own price effect $\xi_1 p_j$ and a contextual reference price effect. The weight $\omega \in [0,1]$ captures the relative impact of own price and contextual reference price on the decision maker's utility. Plugging in the mean price $p_n = (\sum_{l\in B_n} p_l)/J_n$ and rearranging, we have

$$\begin{aligned} v_j &= \alpha_j + \beta x_j + \gamma\left(\sum_{l\in B_n} x_l\right) + \omega\xi_1 p_j \\ &\quad + (1-\omega)\xi_2\left(p_j - \frac{\sum_{l\in B_n} p_l}{J_n}\right) \\ &= \alpha_j + \beta x_j + \gamma\left(\sum_{l\in B_n} x_l\right) + (\omega\xi_1 + (1-\omega)\xi_2)p_j \\ &\quad + \frac{(\omega-1)\xi_2}{J_n}\left(\sum_{l\in B_n} p_l\right). \end{aligned}$$

The model above is not identified because we have three parameters (ω, ξ_1, ξ_2) for two covariates. Defining $\beta_p = \omega\xi_1 + (1-\omega)\xi_2$ and $\gamma_p = (\omega-1)\xi_2/J_n$, we can re-parameterize the utility function as

$$v_j = \alpha_j + \beta x_j + \gamma\left(\sum_{l\in B_n} x_l\right)\beta_p p_j + \gamma_p\left(\sum_{l\in B_n} p_l\right).$$

Similar to the case of promotional effects discussed previously, the term $\gamma_p(\sum_{l\in B_n} p_l)$ in the model specification gives us a general framework for empirical work. If $\gamma_p = 0$ (this may be because $\omega = 1$ or $\xi_2 = 0$) we may conclude the absence of contextual reference price effects, hence there are no spillover effects of price. On the other hand, $\gamma_p > 0$ indicates that reference price affects utility.

If we redefine x_j to include p_j, the utility derived from alternative j is simplified as

$$\begin{aligned} U_j &= v_j + \varepsilon_j \\ &= \alpha_j + \beta x_j + \gamma\left(\sum_{l\in B_n} x_l\right) + \varepsilon_j, \end{aligned}$$

where the random component ε_j is assumed to have the cdf

$$\exp\left(-\sum_{n=1}^{N}\left(\sum_{l\in B_n} e^{-\varepsilon_l/\delta_n}\right)^{\delta_n}\right).$$

This results in the choice probability for alternative j in nest n to be

$$P_j = \frac{e^{v_j/\delta_n}(\sum_{l\in B_n} e^{v_l/\delta_n})^{\delta_n-1}}{\sum_m(\sum_{g\in B_m} e^{v_g/\delta_m})^{\delta_m}}.$$

As noted previously, in addition to incorporating spillover effects, the proposed demand system also relaxes the IPS restriction. This can be seen by the substitution ratio $(-\partial P_k/\partial x_{ja})/(\partial P_j/\partial x_{ja})$ derived below (a proof is provided in Online Appendix 1 (available as supplemental material at http://dx.doi.org/10.1287/mksc.2014.0886)), which represents the proportion of the increase in expected demand for alternative j that is generated by substitution away from alternative k following an improvement to attribute x_{ja}:

$$\frac{-\partial P_k/\partial x_{ja}}{\partial P_j/\partial x_{ja}} = \begin{cases} \dfrac{-P_k(((\delta_n-1)P_{j\mid B_n} - \delta_n P_j)\beta_a + (1-P_n)\delta_n\gamma_a)}{P_j((1+(\delta_n-1)P_{j\mid B_n} - \delta_n P_j)\beta_a + (1-P_n)\delta_n\gamma_a)} \\ \qquad\qquad \text{for } k\neq j, \text{ and } k, j\in B_n \\ \dfrac{\delta_n P_k(P_j\beta_a + P_n\gamma_a)}{P_j((1+(\delta_n-1)P_{j\mid B_n} - \delta_n P_j)\beta_a + (1-P_n)\delta_n\gamma_a)} \\ \qquad\qquad \text{for } k\neq j, \text{ and } k\in B_m,\ j\in B_n. \end{cases}$$

Regardless of whether k is from the same nest or a different nest than j, the substitution ratio depends on marketing instrument specific parameters, β_a and γ_a. In our formulation, the spillover term must be restricted to a nest that does not include all alternatives to break the IPS restriction. Otherwise, the spillover term will have no impact on the maximum utility and would drop out of the choice probability.

Our approach of using the summation (or mean) of attributes for alternatives within a nest provides an intuitive and parsimonious way to capture spillover across related brands. Alternative approaches to define spillover and break IPS are possible. If a brand's marketing instruments can spill over to brands in more than one nest to varying degrees, one could adopt a hierarchical nesting structure wherein both the attribute summations over the "child" nest that includes the brand, and the "parent" nest that contains the child nest and other related nests, are used separately to allow for a more flexible spillover effect. Choosing between alternative nesting structures has typically been based on researchers' prior beliefs about consumer behavior, combined with considerations of model fit. As an alternative to a summation or mean, Ching et al. (2009) use an indicator variable that takes value 1 if any brand in the category is on feature or display, to capture the consumer's category consideration. In the context of price spillover, one useful alternative definition is the minimum price of brands in a nest. In our application to consumer packaged goods, we empirically investigate this alternative form of spillover for price.

2.3. Benchmark Models and Heterogeneity

We will benchmark the CASFL model against several of the workhorse RUM models including the NL, GNL, and RC logit. These models achieve greater flexibility in substitution patterns than the logit by assuming more general error structures and by allowing for taste heterogeneity. The NL model allows brands in different nests to have substitution patterns that are not proportional to market shares. The GNL model goes further to allow a more flexible substitution pattern across alternatives. In the GNL, each alternative can be part of more than one nest to varying degrees (probabilistic membership). This flexible nest structure relaxes the IIA restriction that is found within the predefined nest structure in a standard NL model.

In a GNL, an allocation parameter τ_{jn} reflects the extent to which alternative j belongs to nest n. Two conditions are imposed on the allocation parameters: $\tau_{jn} \geq 0\ \forall j, n$ and $\sum_n \tau_{jn} = 1\ \forall j$. For each nest, an inclusive value δ_n captures the degree of independence among alternatives within the nest. The higher δ_n, the greater is the independence. Define

$$v_j = \alpha_j + \beta x_j.$$

Table 1 Hypothetical Example of Aggregation and IPS

Consumer	Brand	Original choice probability	Choice probability after instrument I1 improves	Proportion drawn from *B*2 and *B*3	Choice probability after instrument I2 improves	Proportion drawn from *B*2 and *B*3
Consumer 1	*B*1	8/32	14/32		20/32	
	*B*2	10/32	8/32	1/3	6/32	1/3
	*B*3	14/32	10/32	2/3	6/32	2/3
Consumer 2	*B*1	10/32	22/32		16/32	
	*B*2	16/32	8/32	2/3	12/32	2/3
	*B*3	6/32	2/32	1/3	4/32	1/3
Total	*B*1	9/32	18/32		18/32	
	*B*2	13/32	8/32	5/9	9/32	4/9
	*B*3	10/32	6/32	4/9	5/32	5/9

The probability that a consumer chooses alternative j given by the GNL model is

$$P_j = \frac{\sum_{n=1}^{N}(\tau_{jn}e^{v_j})^{1/\delta_n}(\sum_{l\in B_n}(\tau_{ln}e^{v_l})^{1/\delta_n})^{\delta_n-1}}{\sum_{m=1}^{N}(\sum_{g\in B_m}(\tau_{gm}e^{v_g})^{1/\delta_m})^{\delta_m}}.$$

In the GNL, as long as two alternatives do not belong to the same nest with probability 1, IIA does not hold. While the GNL provides a higher degree of flexibility in substitution between pairs of alternatives than both the NL and the standard logit, this relaxation does not help address the IPS restriction. Bierlaire (2006) provides a proof that the GNL is a member of the generalized extreme value (GEV) family, and Steenburgh (2008) proved that all GEV models suffer from IPS.

Heterogeneous choice models allow a wider variety of substitution patterns to occur among alternatives than their homogeneous counterparts. This does not mean, however, that these models solve the problems associated with the IPS property in a meaningful way. As we will show in our empirical analysis, imposing IPS precludes reasonable individual choice behavior and limits the substitution patterns that can be found. In contrast, the CAFSL model allows a wider variety of choice behavior to be recovered because it relaxes IPS at the individual level.

In Table 1, we illustrate how adding taste heterogeneity to a choice model allows for greater flexibility. Suppose two consumers with different tastes make brand choices from the set $\{B_1, B_2, B_3\}$. Brand $B1$ uses two different marketing instruments I1 and I2. The proportion of demand drawn by brand $B1$ from brands $B2$ and $B3$ is the same for both instruments, for each consumer. This implies that the choices of each consumer conform to IPS. However, for the market as a whole (i.e., the aggregation of the two consumers' choices), instrument I1 draws more market share from $B2$, while instrument I2 draws more market share from $B3$.

This is not entirely satisfying. While heterogeneity may provide more flexible substitution patterns in aggregate, it does not eliminate the possibility that even greater gains can be made by allowing a wider variety of individual choice behavior. From a substantive perspective, the increased availability of individual consumer panel data and the development of hierarchical Bayesian estimation techniques have facilitated direct targeting of consumers at the individual level. For example, Rossi et al. (1996) show that individual-level targeting can achieve substantial gains even with rather short purchase histories. As individual-level targeting becomes more popular in practice, it becomes increasingly important that individual-level models be correctly and flexibly specified. Furthermore, our empirical results suggest that correctly modeling individual choice behavior can also improve aggregate results.

Given the well documented existence of heterogeneity in consumers' preference, we extend both our proposed model and the benchmark models to incorporate a random coefficient framework (Bayesian hierarchical structure) to account for individual differences. We add subscript i to represent an individual consumer (or physician in our pharmaceutical case) and h to represent the consumer's hth store trip (or hth patient visit in our pharmaceutical case).

In particular, we specify the following utility functions for the RC logit and RC GNL:

$$U_{ijh} = \alpha_{ij} + \beta_i x_{ijt(h)} + \varepsilon_{ijh} \quad \forall\, j \neq 0 \quad \text{and} \quad V_{i0h} = \varepsilon_{i0h},$$

where $t(h)$ represents the time of hth decision occasion and U_{i0h} is the utility of no-purchase. Letting $\theta_i = \{\alpha_{i1}, \ldots, \alpha_{iJ}, \beta_i\}$, we specify a Bayesian hierarchical structure (random coefficient) by assuming that $\theta_i \sim N(\theta, \Sigma)$.

For the RC CAFSL model we specify

$$U_{ijh} = \alpha_{ij} + \beta_i x_{ijt(h)} + \gamma_i\left(\sum_{k\in B_n} x_{ikt(h)}\right) + \varepsilon_{ijh} \quad \forall\, j \neq 0 \quad \text{and}$$

$$U_{i0h} = \varepsilon_{i0h}.$$

Letting $\theta_i = \{\alpha_{i1}, \ldots, \alpha_{iJ}, \beta_i, \gamma_i\}$, we specify a Bayesian hierarchical structure (random coefficient) by assuming $\theta_i \sim N(\theta, \Sigma)$.

Table 2 IIA and IPS Properties of Proposed and Benchmark Models

	Logit	NL	GNL	CAFSL	RC logit
Does IIA hold?	Yes	Holds only within nests	No	Holds only within nests	Yes, at the individual level. Aggregation across heterogeneous consumers implies that aggregate substitution rates are not literally constrained by IIA.
Does IPS hold?	Yes	Yes	Yes	No	Yes, at the individual level. Aggregation across heterogeneous consumers implies that aggregate substitution rates are not literally constrained by IPS. However, our example and simulation experiment show there is insufficient relaxation of the constraint.

Let y_{ijh} indicate the choice of alternative j by decision maker i for decision occasion h. The joint posterior distribution of the parameters conditional on the data is given by the following expression for all three models:

$$L \propto \left[\prod_{i=1}^{I}\left[\prod_{j=1}^{J}\prod_{h=1}^{H_i}(P_{ijh})^{y_{ijh}}\right] f(\theta_i \mid \theta, \Sigma)\right] f(\theta, \Sigma),$$

where for the RC logit,

$$P_{ijh} = \frac{e^{v_{ijh}}}{\sum_l e^{v_{ilh}}}$$

for the RC GNL,

$$P_{ijh} = \frac{\sum_{n=1}^{N}(\tau_{jn} e^{v_{ijh}})^{1/\delta_n}(\sum_{l\in B_n}(\tau_{ln} e^{v_{ilh}})^{1/\delta_n})^{\delta_n - 1}}{\sum_{m=1}^{N}(\sum_{g\in B_m}(\tau_{gm} e^{v_{igh}})^{1/\delta_m})^{\delta_m}}$$

and for the RC CAFSL,

$$P_{ijh} = \frac{e^{v_{ijh}/\delta_n}(\sum_{l\in B_n} e^{v_{ilh}/\delta_n})^{\delta_n - 1}}{\sum_m (\sum_{g\in B_m} e^{v_{igh}/\delta_m})^{\delta_m}}.$$

To assess the extent to which a standard RUM model with parameter heterogeneity can capture non-IPS substitution patterns, we conduct a simulation experiment, details of which are presented in Online Appendix 2. In the experiment, we generate data from the RC CAFSL, and then estimate the true model and two strong benchmark models: RC MNL and RC GNL. The simulation results show that the benchmark models are incapable of accurately recovering the true substitution patterns between competing brands when marketing instruments have spillover effects.

Horowitz (1991) raised the concern that increased flexibility of the error structure specification might discourage modelers from pursuing the development of enhanced utility function specifications. This concern seems to apply in the case of IPS. Our simulation study shows that without structurally accounting for spillover effects, taste heterogeneity alone does not provide enough flexibility to recover the substitution patterns found in the data.

In Table 2 we summarize the main properties of the proposed and benchmark models in terms of restrictions imposed on the substitution patterns. The key observation is that only the proposed model relaxes the IPS restriction at the individual and aggregate levels.

3. Data

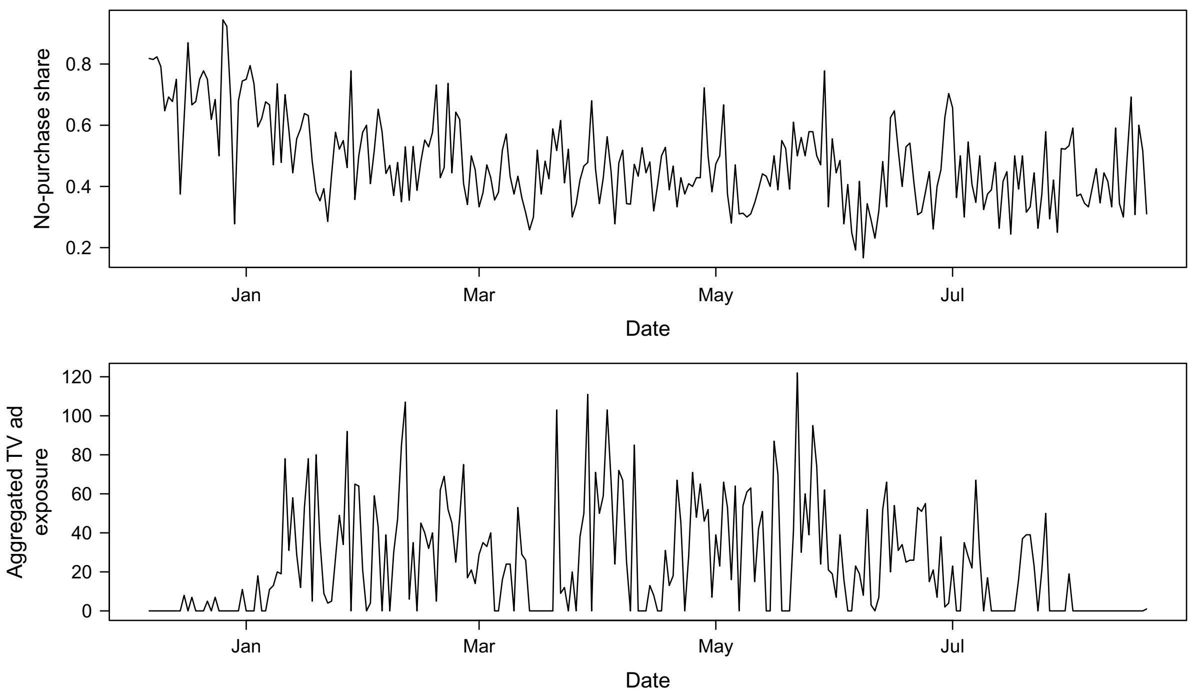
We examine differences in share stealing across marketing instruments in two different empirical settings: consumer packaged goods (CPG) and prescription pharmaceuticals. As we describe next, the sets of marketing instruments that are commonly used in the two contexts are very different. This helps to illustrate the generalizability of our proposed model.

3.1. Consumer Packaged Goods (CPG) Market

Commonly used marketing instruments in most CPG product categories include retail price, in-store displays, retailer feature advertising, and manufacturer TV advertising. We focus on yogurt, a category that has been extensively studied in the marketing academic literature, and use AC Nielsen consumer panel data for the Springfield, MO market. There is no in-store display activity because of the perishability of products in this category. We consider four brand options, i.e., Dannon, Yoplait, other national brands, and a store brand, plus the option of "no (yogurt) purchase." Purchases of multiple flavors of a brand on a given shopping occasion are grouped together as a single brand choice outcome. Store visits of households that had a telemeter connected to their TV set and that purchased yogurt more than three times in the one-year period of the data were included. Data of the first 97 days for each household are used to initialize an advertising stock variable (discussed subsequently). The remaining 258 days are used for model estimation. This results in a sample of 334 households who made 6,586 store trips.

In Figure 1 we show the aggregate share of "no purchase" and aggregated (across households) exposures to yogurt TV advertising over the estimation sample period. The plots reveal that in the first month or so of the data, the share of no-purchase is high and TV advertising exposures are low. This suggests the possibility that TV advertising has category-expanding effects. However, since the first month of the data also coincides with winter, we consider the possibility of seasonality in yogurt purchasing and firms strategically lowering their TV advertising spending in the winter season. To control for this we include in all models the daily temperature (the midpoint between

Figure 1 No-Purchase Share and Aggregate TV Advertising Exposures



the daily low and high) of Springfield, MO as a common attribute for all brands.

In Table 3 we provide descriptive statistics of the data. About 48% of store visits do not result in yogurt purchases. Dannon has the largest market share, followed closely by Yoplait and other national brands. Dannon also has the highest price, but the lowest levels of retailer feature advertising and TV advertising. Store brands do not advertise on TV but have the highest level of retailer feature advertising. The impact of TV advertising is expected to carry over from one period to the next with deteriorating effectiveness. To capture the long-term effect, we follow the advertising model of Nerlove and Arrow (1962) and formulate a "TV Adstock" variable, which is defined as $TV\ Adstock_{ijt} = \tau \cdot TV\ Adstock_{ijt-1} + TV_{ijt}$, where TV_{ijt} is the number of exposures to TV ads for brand j received by household i on day t, and τ is a carryover parameter that lies between 0 and 1.

3.2. Pharmaceutical Market

While there are multiple constituencies that determine demand for a brand drug, pharmaceutical firms in the United States devote most of their marketing resources primarily to influence two groups: physicians and patients.[3] Pharmaceutical manufacturers spent at least $20.5 billion on promotional activities in 2008, excluding sampling. Of that, $12 billion went to detailing to physicians, $4.7 billion to direct-to-consumer-advertising (DTCA), and $3.4 billion to meetings and events (M&E) (Congressional Budget Office 2009). Similar to previous research (Gönül et al. 2001, Ching and Ishihara 2012, Chan et al. 2013), we assume that physicians write prescriptions exclusively for the welfare of their patients based on their professional judgments. Physicians' preference for improving patients' well-being is due to a sense of professional integrity, a desire for good reputation, and a fear of malpractice suits.

We expect to find different competitive impacts when firms invest in detailing, M&E, and DTCA because these marketing instruments work in very different ways. Detailing is personal selling to physicians by representatives of pharmaceutical firms. The representatives inform physicians about drug efficacy and safety, answer physicians' questions, establish and maintain good will of the brand, and provide physicians with drug samples. Firms have full control of what to communicate with physicians as long as messages conform to Food and Drug Administration (FDA) regulations and these communications take place behind closed doors. Given this, we might expect a high proportion of growth from detailing to come at the expense of competing brands.

In contrast, pharmaceutical firms also sponsor professional meetings and events, including some that offer physicians credit for continuing medical education. Firms may help fund, organize, and advertise

[3] In pharmaceutical markets, individual-level targeting is mainly at the physician level since physicians are primary decision makers for prescriptions. In addition, physician-level prescription data are made available by marketing research firms such as Impact-Rx or IMS Health, while patient-level data are often hard to obtain because of privacy laws.

Table 3 Summary Statistics of Yogurt Data for 334 Panel Households

Brand shares (6,586 store trips)	Brand	Share
	Dannon	0.165
	Yoplait	0.148
	Other brands	0.140
	Store brands	0.068
	No purchase	0.479
Marketing instruments (6,586 store trips)	**Mean**	**Std dev**
Price ($/unit)		
Dannon	0.819	0.111
Yoplait	0.673	0.062
Other brands	0.531	0.114
Store brands	0.425	0.038
Feature (proportion of trips)		
Dannon	0.045	0.207
Yoplait	0.050	0.217
Other brands	0.076	0.264
Store brands	0.166	0.372
TV advertising[1] (proportion of days with exposure)		
Dannon	0.019	0.136
Yoplait	0.028	0.165
Other brands	0.024	0.151
Store brands	0	0
Daily temperature	54.607	20.697

[1]Descriptive statistics of advertising are calculated across 334 households × 355 days.

M&E, and may also subsidize attendance of physicians. Unlike detailing, firms can only influence the topics that are discussed in M&E indirectly through M&E organizers. As a consequence, the content of M&Es tends to be disease-oriented, different from the brand-oriented communications in detailing. In addition, discussion and interaction among attendees makes M&E attendance a different experience for physicians relative to detailing.

Traditionally, a negligible part of the overall marketing budget was spent on influencing patients. However, in the last decade this component has been growing rapidly in the form of DTCA. DTCA can expand the category via the informational and educational roles of advertising. Advertising can inform potential patients of the existence of a health condition, possible symptoms and consequences, as well as the availability of a treatment. Better informed under-diagnosed or under-treated patients, in turn, will understand their health conditions better, and may be prompted to seek medical consultation by visiting a physician. This perspective suggests that an important source of sales gains due to DTCA is newly diagnosed patients, who expand overall category demand that potentially benefits all competing firms. Another role of DTCA is to persuade patients to ask their physicians for specific brand name drugs. The literature suggests that patient requests do influence physicians' prescription behavior. As a consequence, sales gains occur due to physicians' switching from competing brands, but also due to switching from nondrug prescriptions. The latter is a source that expands the category.

The therapeutic class that we use in this study is statins (or HMG-CoA reductive inhibitors).[4] Statins are drugs used to lower cholesterol levels in people at risk for cardiovascular disease because of hyperlipidemia. During the period spanned by our data (2002–2004), there are four major statins available for prescription: Lipitor produced by Pfizer, Zocor by Merck, Pravachol by Bristol-Myers Squibb (BMS) and Crestor by AstraZeneca. Nondrug only treatment is also a common prescription issued by physicians if the patient's diagnosed condition does not warrant drug treatment. Nondrug treatment methods include healthy eating, quitting smoking, increasing physical activity, moderating alcohol intake, and maintaining an ideal body weight.

Data on patient visits, prescriptions written by physicians, and detailing and M&E to which the physicians are exposed, are available for a panel of 247 physicians in the United States over a 24-month period, June 2002 to May 2004. The data were made available by a marketing research firm, ImpactRx, Inc. The firm runs a panel consisting of a representative sample of the universe of physicians in the United States, balanced across geographic regions, physician specialties, and prescription volumes. The monthly data on physician-level patient visits, number of prescriptions written for each alternative, number of detailing visits received, and number of M&Es attended, are combined with data on monthly DTCA expenditures by alternative, obtained from Kantar Media Intelligence. We link the ImpactRx panel data to Designated Media Area (DMA) level DTCA monthly expenditures in the Kantar data via physician-level zip codes. DTCA is measured as $-expenditure per capita per month based on the population of the designated market area (DMA). Because we do not observe patient characteristics, and because marketing instruments are only observed at monthly intervals, we can generate individual choice data from the monthly alternative-level number of prescriptions written.[5] Therefore, we assume in our model that

[4] We do not include a price term in the utility function for two reasons. First, high cholesterol treatment is typically paid for through insurance or patient assistance programs. Second, statin drug prices remained stable in our study period.

[5] To illustrate, suppose we observe that a physician in a given month wrote three prescriptions for Lipitor, two for Zocor, one for Crestor, and two for nondrug treatment. We treat these data as eight prescription choice occasions for this physician; on three occasions Lipitor was chosen, on two Zocor was chosen, on one Crestor was chosen, and on two nondrug treatment was chosen. Note that the time ordering of these individual choices within a month does not matter because the marketing expenditures do not vary across occasions within a month for a given physician.

Table 4 Summary Statistics of Statins Data

Prescription shares (5,121 patient visits)	Brand	Share
	Lipitor	0.287
	Zocor	0.150
	Pravachol	0.105
	Crestor	0.228
	Non-drug treatment	0.231
Marketing instruments[1]	Mean	SD
Detailing (number of detailing visits)		
Lipitor	0.634	1.035
Zocor	0.728	1.128
Pravachol	0.366	0.746
Crestor	0.960	1.316
DTCA ($ per capita)		
Lipitor	0.040	0.016
Zocor	0.028	0.009
Pravachol	0.008	0.009
Crestor	0.023	0.039
M&E (number of meetings and events)		
Lipitor	0.031	0.202
Zocor	0.006	0.079
Pravachol	0.004	0.064
Crestor	0.047	0.227

[1]Descriptive statistics are calculated across 247 physicians × 24 months.

all patient visits to a given physician in a particular month have the same deterministic utility for a prescription option.

In Table 4 we present summary statistics of the data. About one-quarter of visits receive prescriptions for nondrug treatment instead of a drug treatment. Among the four drugs, Lipitor is the market leader with a market share of 28.7%, followed by Crestor, Zocor, and Pravachol. As shown in Table 4, on average, there are more detailing visits and M&E for Crestor than for the other three brands. However, DTCA expenditure on Lipitor is the largest among the four brands.

Similar to the yogurt application, here we introduce a vector of stock variables for marketing instruments $x_{ijt} = [x^1_{ijt}, x^2_{ijt}, x^3_{ijt}]$,

$$\begin{aligned} x^1_{ijt} &= \lambda_1 x^1_{ijt-1} + DET_{ijt}, \\ x^2_{ijt} &= \lambda_2 x^2_{ijt-1} + ME_{ijt}, \\ x^3_{ijt} &= \lambda_3 x^3_{ijt-1} + DTC_{ijt}, \end{aligned}$$

where DET_{ijt} is the number of detailing visits by drug j to physician i in month t; ME_{ijt} is the number of M&Es sponsored by drug j that received participation by physician i in month t; DTC_{ijt} is drug j's DTCA per capita \$-expenditure in physician i's DMA area in month t; and λ is the carryover parameter with a value between 0 and 1. We use the first 14 months of data to initialize the three marketing instrument stock variables and the remaining 10 months to estimate the models.

4. Results

To estimate the carryover parameters for marketing instruments, we conducted a grid search and used the maximized log-likelihood of a logit model to make our final selection of parameter values for the yogurt data and the statins data separately. This led to the following estimated values of the carryover parameters: 0.97 for TV ads per day in the yogurt data; 0.75 for detailing per month, 0.90 for M&E per month, and 0.75 for DTCA per month in the statins data.[6] These are quite close to the findings reported in the previous literature. For example Narayanan et al. (2004) reports carryover values of detailing and M&E at 0.86 each, and DTCA at 0.75.

Similar to Bucklin et al. (1998) and Bell et al. (1999), we divide the choice set into two nests for the CAFSL model, for both applications. One nest contains the nopurchase or nondrug treatment option, and the other contains the four brands. We also fit two RC GNL models for each application: One model has two nests (the nest for all brands and the nest for the nopurchase/nondrug treatment option), and the other model has three nests (the nest for all brands, the nest for all alternatives including nopurchase/nondrug treatment, and the nest for the nopurchase/nondrug treatment option only).

4.1. Yogurt Results

We show parameter estimates and model fit statistics of the three models in Table 5. We find that the RC GNL with three nests outperforms the model with two nests and therefore report results only for the three-nest model. The log marginal likelihood values indicate that the RC CAFSL model fits the data best, followed by the RC GNL model, and the RC logit.

For all three models, we find a positive effect of daily temperature on brand utilities, suggesting that yogurt demand rises with warmer temperatures. We also find evidence of significant heterogeneity across consumers in their preferences for different brands and responsiveness to marketing instruments (variance-covariance matrices are shown in Online Appendix 2 Tables A8–A10).

In all models, we find negative price effects and positive feature effects. We find positive effects of TV ads for the RC logit and RC GNL models. Interestingly, the CAFSL model yields a positive effect of TV ad stock summation but not a direct effect of each brand's TV ad stock. This suggests that TV advertising serves to benefit brands primarily by expanding the category. As to price, we find that the own price is negative as expected and the price spillover effect

[6] We also estimated the carryover parameters based on the nested logit and CAFSL models, but found no significant difference in results.

Table 5 Yogurt Data—Parameter Estimates for RC Models

	RC logit		RC GNL		RC CAFSL	
Variables	Mean	95% interval	Mean	95% interval	Mean	95% interval
Brand intercepts						
Dannon	0.543	(0.009, 1.068)	0.654	(0.253, 1.081)	−1.315	(−1.948, −0.804)
Yoplait	−0.202	(−0.702, 0.491)	0.111	(−0.223, 0.474)	−1.904	(−2.561, −1.364)
Other Nat.	−0.996	(−1.502, −0.343)	−0.320	(−0.667, 0.033)	−2.514	(−3.200, −1.957)
Store Br.	−2.524	(−3.118, −1.907)	−1.067	(−1.385, −0.752)	−3.659	(−4.363, −3.090)
Instruments and daily temperature						
Price	−3.834	(−4.656, −3.220)	−3.318	(−3.899, −2.728)	−3.506	(−4.148, −2.857)
Feature	1.572	(1.479, 1.680)	0.794	(0.629, 0.941)	1.014	(0.858, 1.149)
TV Ads	0.075	(0.010, 0.134)	0.039	(0.002, 0.071)	—[1]	—
Temp.	0.015	(0.010, 0.021)	0.015	(0.010, 0.020)	0.015	(0.010, 0.020)
Summation of instruments						
Price	—	—	—	—	0.873	(0.571, 1.195)
Feature	—	—	—	—	—	—
TV Ads	—	—	—	—	0.071	(0.033, 0.114)
Inclusive value						
δ_1	—	—	0.701	(0.524, 0.815)	0.581	(0.490, 0.671)
δ_2	—	—	0.064	(0.031, 0.110)	—	—
Probability of membership in the nest of all brands + No purch						
Dannon	—	—	0.104	(0.050, 0.163)	—	—
Yoplait	—	—	0.165	(0.060, 0.262)	—	—
Other Nat.	—	—	0.811	(0.714, 0.876)	—	—
Store Br.	—	—	0.896	(0.814, 0.942)	—	—
No Purch	—	—	0.027	(0.011, 0.047)	—	—
Log-ML[2]	−6,222		−6,115		−6,095	

[1]The own-effect of TV ads is not significant, hence the model was reestimated after leaving this variable out.
[2]Log marginal likelihood.

Table 6 Substitution Matrix and Elasticities (for Dannon) for Yogurt Data

	RC logit model			RC GNL model			RC CAFSL model		
	Price	Feature	Ad	Price	Feature	Ad	Price	Feature	Ad
Dannon	—	—	—	—	—	—	—	—	—
Yoplait (%)	13.1	22.9	14.4	23.8	33.5	19.2	23.2	30.5	0
Other Nat.	17.9	14.8	21.5	20.6	14.1	27.1	41.2	21.6	0
Store Br.	15.9	8.2	4.2	10.6	6.7	9.9	34.8	10.8	2.1
No Purch	53.1	54.1	59.9	45.0	45.6	47.7	0.8	37.1	97.9
Total	100	100	100	100	100	100	100	100	100
Elasticity	−1.665	0.042	0.037	−1.924	0.029	0.025	−1.94	0.039	0.022

Notes. For each model, cell entries in each column indicate the percentage of sales increase of Dannon due to a 1% increase in its marketing instrument (e.g., Ad) that is drawn from the alternative indicated in the row. For example, the RC logit model predicts that if Dannon increases its Ad by 1%, 14.4% of its incremental sales will come from Yoplait.

is positive. This finding indicates that consumers tend to use the mean price of the category as a reference to evaluate the observed price.[7]

In Table 6 we present own elasticities for Dannon (as an illustration) and the substitution matrix showing sources of gains for Dannon from each of its three marketing instruments. Note that the elasticity of demand is greatest from price (ranging from −1.665 to −1.940), followed by feature and TV advertising.

The three models predict very different substitution patterns among brands. Just as we saw in the simulation study, neither the RC logit nor the RC GNL model fully overcomes the IPS restriction. As a result, the proportion of demand drawn from a given brand is much closer across the three instruments under these models, relative to the outcome under the CAFSL. In particular, we see that the incremental demand drawn from category expansion falls in a relatively tight range, varying from 53.1% to

[7] We also estimate a model in which consumers use the minimum price in the category as the reference point and find the model fit is not as good as that of our proposed model.

59.9% in the RC logit and from 45.0% to 47.7% in the RC GNL model. These values fall close to the share of no purchase in the data (48%). By contrast the CAFSL model predicts that gains from category expansion differ dramatically between the three marketing instruments. Of Dannon's incremental demand due to price, less than 1% is drawn from the nonpurchase option. In sharp contrast, most of the incremental demand created by TV ads, 97.9%, is drawn from the no-purchase option. The gains due to category expansion created by feature ads fall in the middle at 37.1%.

These results suggest that Dannon's TV advertising benefits competing brands. Such strong positive spillover of TV ads is intuitive in a category such as yogurt. An important selling point of yogurt is its potential health benefits, e.g., probiotics (good bacteria). Firms therefore have a strong incentive to focus on these benefits in their advertising to educate and inform health conscious consumers. For example, Dannon's iconic TV campaign, "Old People in Russia," purported that Soviet Georgians lived to over 100 because they ate a lot of yogurt. This persuasive positive information about yogurt delivered by Dannon's humorous campaign potentially benefitted not only Dannon but also competing yogurt brands.

Furthermore, these results have important managerial implications. Suppose a brand manager is trying to decide whether to invest marketing dollars in a 10% decrease in price versus TV advertising. The estimated elasticity implies that a 10% decrease in the level of price will yield a 19.4% increase in demand, whereas a 10% increase in the level of TV advertising will yield only a 0.22% increase in demand. Assuming (for purposes of this example) that the costs of the two alternative incremental activities are the same, we would much rather invest in price reduction than in TV advertising. However, 99.2% of the demand created by pricing is stolen from competing brands, meaning that the demand for Dannon increases by 19.24% by stealing demand away from other brands; 0.16% comes from expanding the category. By contrast, 97.9% of the demand created by TV ads comes from category expansion. This means that the demand for Dannon increases by only 0.005% by stealing demand away from other brands and 0.215% comes at the expense of the no-purchase option. Thus, it would seem that competing brands would have a greater incentive to retaliate if the Dannon brand manager invests in pricing than if she invests in TV ads. Although we do not intend to model the supply side of the industry, a simple correlation analysis of the marketing instruments of different brands is insightful. We find that pairwise correlations of prices of the four brands in our data are all positive, ranging from 0.174 to 0.354, suggesting that firms tend to compete head-to-head on price. On the other hand, we do not find such a consistent pattern for feature and TV advertising in our data.

4.2. Statins

Estimation results are presented in Table 7. In the statins market we find that the RC GNL with two nests outperforms the model with three nests and therefore report results only for the two-nest model. All three models find positive effects of detailing, DTCA, and M&E on physicians' probability of prescribing the marketed drug. The RC CAFSL model finds that the summations of DTCA and M&E have positive effects, suggesting a category expanding effect. By contrast, we do not find a significant effect for the summation of detailing, suggesting that gains from detailing arise primarily from business stealing. In all models, we find evidence of significant heterogeneity across physicians in their preferences for different drugs and responsiveness to marketing instruments (variance-covariance matrices are shown in Online Appendix 2 Tables A11–A13 for reasons of space). Furthermore, we find that the RC CAFSL fits the data best, followed by the RC GNL, and then the RC logit.[8]

In Table 8 we present the own elasticities for Lipitor (as an illustration) and the substitution matrices. As was the case for the yogurt data, the elasticities show that each model comes to roughly the same conclusion about the ability of marketing instruments to generate demand for Lipitor. The elasticity is greatest for detailing (close to 0.28 for all three models) while the elasticities for DTCA and M&E for all three models are considerably smaller.

Nevertheless, the models again come to very different conclusions about the substitution patterns among drugs. The RC logit model implies that the proportion of demand drawn from the nondrug treatment is 20.9% from detailing, 32.8% from M&E, and 27.3% from DTCA. Similarly, the RC GNL implies that the proportion of demand drawn from the nondrug treatment is 14.7% from detailing, 23.6% from M&E, and 24.7% from DTCA. By contrast, the RC CAFSL model shows that 81.6% of the incremental demand created by detailing is stolen from competing drugs. Yet, the opposite occurs for the other marketing instruments. Most of the incremental demand created by DTCA and M&E is drawn from the nondrug treatment (59.8% and 50.3%, respectively).

[8] One may wonder whether there are factors that drive increases over time in both drug use and marketing instruments (such as DTCA and M&E). If so, the category expanding effect we estimate might be spurious. To examine whether there are such missing factors, we add a time trend to the model. We tried a linear time trend and a log transformation of a linear time trend. Neither was statistically significant, which alleviated our concern.

Table 7 Statins Data—Parameter Estimates for RC Models

	RC logit		RC GNL		RC CAFSL	
Variables	Mean	95% interval	Mean	95% interval	Mean	95% interval
Brand intercept						
Lipitor	−0.036	(−0.24, 0.157)	0.054	(−0.095, 0.231)	−0.113	(−0.341, 0.080)
Zocor	−0.926	(−1.194, −0.667)	−0.298	(−0.462, −0.146)	−0.900	(−1.151, −0.668)
Pravachol	−1.467	(−1.796, −1.143)	−0.46	(−0.648, −0.277)	−1.358	(−1.717, −1.060)
Zocor	−0.828	(−1.085, −0.564)	−0.21	(−0.386, −0.058)	−0.860	(−1.121, −0.593)
Instruments						
Detailing	0.147	(0.105, 0.179)	0.071	(0.05, 0.098)	0.134	(0.108, 0.167)
M&E	0.245	(0.124, 0.367)	0.14	(0.085, 0.198)	0.252	(0.175, 0.368)
DTCA	2.363	(1.93, 2.933)	0.812	(0.493, 1.309)	1.928	(1.381, 2.286)
Summation of instruments						
Detailing	—	—	—	—	—	—
M&E	—	—	—	—	0.358	(0.184, 0.530)
DTCA	—	—	—	—	2.160	(1.585, 3.021)
Inclusive value						
δ_1	—	—	0.364	(0.258, 0.582)	0.886	(0.782, 0.948)
δ_2	—	—	0.479	(0.375, 0.575)	—	—
Membership in Nest 1						
Lipitor	—	—	0.24	(0.153, 0.337)	—	—
Zocor	—	—	0.299	(0.163, 0.427)	—	—
Pravachol	—	—	0.508	(0.343, 0.628)	—	—
Zocor	—	—	0.448	(0.289, 0.569)	—	—
Non-Drug Treatment	—	—	0.717	(0.613, 0.831)	—	—
Log-ML	−5,894		−5,885		−5,871	

Table 8 Substitution Matrices and Elasticities (for Lipitor) for Statins

	RC logit model			RC GNL model			RC CAFSL model		
	Detailing	M&E	DTCA	Detailing	M&E	DTCA	Detailing	M&E	DTCA
Lipitor	—	—	—	—	—	—	—	—	—
Zocor (%)	26.5	11.2	28.2	29.8	23.5	29.9	27.7	2.1	14.0
Pravachol	13.1	13.5	20.0	13.7	10.9	19.5	16.0	5.2	6.4
Crestor	39.4	42.5	24.6	41.8	42.0	25.9	37.8	42.4	19.9
Non-Drug Treatment	20.9	32.8	27.3	14.7	23.6	24.7	18.4	50.3	59.8
Total (%)	100	100	100	100	100	100	100	100	100
Elasticity	0.283	0.047	0.049	0.270	0.053	0.031	0.279	0.054	0.051

The category expanding effects of DTCA and M&E obtained by the CAFSL model seem reasonable. Some pharmaceutical advertisements create awareness of drug treatments and may also generate patient requests for medication. Donohue et al. (2004, p. 1181) studied how DTCA works for antidepressant drugs and observed that "for conditions like depression, which are associated with social stigma, advertising may reduce negative views associated with treatment" thereby making it easier for patients to request medication. Liu and Gupta (2011) find that DTCA on minor brands leads to (spillover) patient requests for leading brands in the statin market. Furthermore, M&E are typically geared toward disease-oriented communications and allow physicians to speak to one another, which may make the drug companies less willing to draw comparisons between the drugs.

Similar to the case of yogurt, the results have important managerial implications. Both DTCA and M&E draw more market share from nondrug treatment than from competing drugs, hence they are less threatening to competition than the use of detailing. Furthermore, there are implications for public policy that aims to reduce under-treatment and under-diagnosis of hyperlipidemia. To motivate patients, public policy should encourage DTCA instead of detailing and M&E. On the other hand, to motivate physicians, public policy should encourage M&E. Importantly, the significant category expansion effects of DTCA found in our study argue against attempts to further restrict or ban DTCA for these drugs.

5. Conclusions and Future Research

An essential decision facing any brand manager is the choice of marketing instruments to enhance sales of the brand. Different instruments are relevant for different marketing objectives (category demand expansion or market share stealing). Discrete choice models that include the logit, GNL, and probit have been used to analyze how consumers respond to marketing actions in terms of whether to buy (purchase incidence) and which brand to buy (brand choice). However, these models have the IPS property that implies that the proportion of demand generated by substitution away from a given competing alternative is the same, no matter which marketing instrument is used.

With the recognition that marketing activities on brands can have spillover effects on other alternatives in the category, we propose the CAFSL model that allows for such effects. The CAFSL model also relaxes the IPS constraint on implied substitution patterns. We apply the CAFSL model along with two benchmark models, i.e., the RC logit and the RC GNL, in a simulation experiment and two different empirical situations. When data are generated from the CAFSL model in a simulation, we find that the benchmark models produce incorrect substitution patterns and sources of sales gains. In an application to consumer purchases of yogurt we find that TV advertising by individual brands grows the category, an effect that is vastly understated by the benchmark models. Finally, in an application to statin drugs we find that the benchmark models fail to distinguish between the vastly different effects on primary demand growth of DTCA and M&E relative to detailing. In our data the CAFSL model predicts that increases in DTCA and M&E result in sales gains that come primarily from nondrug treatments rather than from other cholesterol lowering drugs. By contrast, the benchmark models predict that for all three marketing instruments, i.e., DTCA, detailing, and M&E, gains would come largely at the expense of competing drugs.

The proposed CAFSL model can help a brand manager develop a more nuanced and precise understanding of how different marketing instruments work, and plan the marketing mix accordingly. For example, the brand manager may place greater emphasis on category expanding instruments such as TV advertising in consumer packaged goods industries, or DTCA and M&E in prescription drug markets, if retaliation by competing brands is a significant concern. The GNL model, by contrast, does not allow such understanding but its flexible nesting approach provides the opportunity to gain insights into market structure, i.e., how brands compete. Because the goal of this study is to develop a parsimonious model that allows for spillovers and relaxes the IPS restriction, we choose to develop our model based on the NL which is popular in marketing. However, future research should look into the possibility of combining the CAFSL and GNL models to develop a more general model that allows for flexibility in substitution via spillovers in marketing effects and probabilistic nesting structures. This kind of specification may be especially valuable in markets where brand managers do not wish to impose a predetermined market structure on competition between brands, and also wish to allow for flexibility in the sets of brands between which spillovers in marketing effects occur. Furthermore, alternative models to capture spillover and overcome IPS could also be explored.

Finally, we follow previous studies and divide alternatives into a nest consisting of brands and a nest of nopurchase. The approach is parsimonious and works well in uncovering category expansion and share impacts of marketing instruments in our applications. Future research could consider more complex nesting structures such as brand-primary or form-primary hierarchies that are appropriate for markets with SKU-level alternatives (see, for example, Kok and Xu 2011).

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2014.0886.

Acknowledgments

The data used in this study were generously provided by AC Nielsen and ImpactRx, Inc. The authors thank the participants of the 2011 INFORMS Marketing Science Conference and the 2014 BBCRST Conference, and the editor, associate editor, and two reviewers for their many helpful comments and suggestions.

References

Anderson SP, Ciliberto F, Liaukonyte J, Regis R (2012) Push-me pull-you: Comparative advertising in the OTC analgesics industry. CEPR Discussion Paper. http://econpapers.repec.org/paper/cprceprdp/8988.htm.

Ansolabehere S, Iyengar S (1997) *Going Negative: How Political Ads Shrink and Polarize the Electorate* (The Free Press, New York).

Batra R, Homer PM (2004) The situational impact of brand image beliefs. *J. Consumer Psych.* 14(3):318–330.

Bell DR, Chiang J, Padmanabhan V (1999) The decomposition of promotional response: An empirical generalization. *Marketing Sci.* 18(4):504–526.

Ben-Akiva M (1973) The structure of travel demand models. Unpublished doctoral dissertation, Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, MA.

Ben-Akiva M (1974) Note on the specification of a logit model with utility functions that include attributes of competing alternatives. Working paper, Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, MA.

Bierlaire M (2006) A theoretical analysis of the cross-nested logit model. *Ann. Oper. Res.* 144(1):287–300.

Block H, Marschak J (1960) Random orderings and stochastic theories of response. Olkin I, ed. *Contributions to Probability and Statistics* (Stanford University Press, Stanford, CA), 97–132.

Bucklin RE, Gupta S, Siddarth S (1998) Determining segmentation in sales response across consumer purchase behaviors. *J. Marketing Res.* 35(May):189–197.

Chan T, Narasimhan C, Xie Y (2013) Treatment effectiveness and side effects: A model of physician learning. *Management Sci.* 59(6):1309–1325.

Ching A, Ishihara M (2012) Measuring the informative and persuasive roles of detailing on prescribing decisions. *Management Sci.* 58(7):1374–1387.

Ching A, Erdem T, Keane M (2009) The price consideration model of brand choice. *J. Appl. Econometrics* 24(3):393–420.

Congressional Budget Office (CBO) (2009) Promotional spending for prescription drugs. Congressional Budget Office, Washington, DC.

Donohue JM, Berndt ER, Rosenthal M, Epstein AM, Frank RG (2004) Effects of pharmaceutical promotion on adherence to the treatment guidelines for depression. *Medical Care* 42(December):1176–1185.

Gönül FF, Carter F, Petrova E, Srinivasan K (2001) Promotion of prescription drugs and its impact on physicians' choice behavior. *J. Marketing* 65(3):79–90.

Horowitz JL (1991) Reconsidering the multinomial probit model. *Transportation Res. Part B* 25(6):433–438.

Just RE, Hueth DL, Schmitz A (2004) *The Welfare Economics of Public Policy: A Practical Approach to Project and Policy Evaluation* (Edward Elgar, Northampton, MA).

Kalwani M, Yim CK, Rinne HJ, Sugita Y (1990) A price expectation model of customer brand choice. *J. Marketing Res.* 26(August):251–262.

Kok AG, Xu Y (2011) Optimal and competitive assortments with endogenous pricing under hierarchical consumer choice models. *Management Sci.* 57(9):1546–1563.

Koppelman FS, Sethi V (2000) Closed-form discrete-choice models. Hensher DA, Button KJ, eds. *Handbook of Transport Modeling* (Pergamon, Amsterdam), 211–225.

Kwoka JE (1993) The sales and competitive effects of styling and advertising practices in the U.S. auto industry. *Rev. Econom. Statist.* 75(4):649–656.

Leeflang PSH, Wittink DR (2001) Explaining competitive reaction effects. *Internat. J. Res. Marketing* 18(1–2):119–137.

Liaukonyte J (2012) Is comparative advertising an active ingredient in the market for pain relief? Working paper, Cornell University, Ithaca, New York.

Liu Q, Gupta S (2011) The impact of direct-to-consumer advertising of prescription drugs on physician visits and drug requests: Empirical findings and public policy implications. *Internat. J. Res. Marketing* 28(3):205–217.

Lovett MJ, Shachar R (2011) The seeds of negativity: Knowledge and money. *Marketing Sci.* 30(3):430–446.

Marschak J (1960) Binary-choice constraints on random utility indicators. Arrow K, Karlin S, Suppes P, eds. *Mathematical Methods in the Social Sciences* (Stanford University Press, Stanford, CA), 312–329.

McFadden D (1981) Econometric models of probabilistic choice. Manski C, McFadden D, eds. *Structural Analysis of Discrete Data with Econometric Applications* (MIT Press, Cambridge, MA), 198–272.

Narayanan S, Desiraju R, Chintagunta PK (2004) Return on investment implications for pharmaceutical promotional expenditures: The role of marketing-mix interactions. *J. Marketing* 68(4):90–105.

Nerlove M, Arrow KJ (1962) Optimal advertising policy under dynamic conditions. *Economica* 29(May):129–142.

Nijs VR, Dekimpe MG, Steenkamp J-BEM, Hassens DH (2001) The category-demand effects of price promotions. *Marketing Sci.* 20(1):1–22.

Rajendran KN, Tellis GJ (1994) Contextual and temporal components of reference price. *J. Marketing* 58(1):22–34.

Rossi PE, McCulloch RE, Allenby GM (1996) The value of purchase history data in target marketing. *Marketing Sci.* 15(4):321–340.

Sahni N (2013) Advertising spillovers: Field-experiment evidence and implications for returns from advertising. Memo, Stanford University, Stanford, CA.

Steenburgh TJ (2008) The invariant proportion of substitution property (IPS) of discrete-choice models. *Marketing Sci.* 27(2): 300–307.

Steenkamp J-BEM, Nijs VR, Hassens DM, Dekimpe MG (2005) Competitive reactions to advertising and promotion attacks. *Marketing Sci.* 24(1):35–54.

Wansink B (1994) Advertising's impact on category substitution. *J. Marketing Res.* 31(November):505–515.

Wen C-H, Koppelman FS (2001) The generalized nested logit model. *Transportation Res. Part B* 35(7):627–641.

Winer RS (1986) A reference price model of brand choice for frequently purchased products. *J. Consumer Res.* 13(September): 250–256.