HARVARD | BUSINESS | SCHOOL

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

Qiang Liu
Thomas J. Steenburgh
Sachin Gupta

Working Paper

12-012

August 31, 2011

The Flexible Substitution Logit: Uncovering Category Expansion and Share Impacts of Marketing Instruments[ab]

Qiang Liu[c]
liu6@purdue.edu

Thomas J. Steenburgh[d]
tsteenburgh@hbs.edu

Sachin Gupta[e]
sg248@cornell.edu

August 31, 2011

[a] The data used in this study were generously provided by ImpactRx Inc. [b] The first two authors contributed equally and are listed alphabetically. [c] Qiang Liu is Assistant Professor of Marketing at the Krannert School of Management at Purdue University. [d] Thomas J. Steenburgh is Associate Professor of Marketing at Harvard Business School. [e] Sachin Gupta is Henrietta Johnson Louis Professor of Management and Professor of Marketing at the Johnson Graduate School of Management, Cornell University.

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

Abstract

Different instruments are relevant for different marketing objectives (category demand expansion or market share stealing). To help brand managers make informed marketing mix decisions, it is essential that marketing mix models appropriately measure the different effects of marketing instruments. Discrete choice models that have been applied to this problem might not be adequate because they possess the Invariant Proportion of Substitution (IPS) property, which imposes counter-intuitive restrictions on individual choice behavior. Indeed our empirical application to prescription writing choices of physicians in the hyperlipidemia category shows this to be the case. We find that three commonly used models that all suffer from the IPS restriction – the homogeneous logit model, the nested logit model, and the random coefficient logit model – lead to counter-intuitive estimates of the sources of demand gains due to increased marketing investments in Direct-to-Consumer Advertising (DTCA), detailing, and Meetings and Events (M&E). We then propose an alternative choice model specification that relaxes the IPS property – the so-called "flexible substitution" logit (FSL) model. The (random coefficient) FSL model predicts that sales gains from DTCA and M&E come primarily from the non-drug treatment (87.4% and 70.2% respectively), whereas gains from detailing come at the expense of competing drugs (84%). By contrast, the random coefficient logit model predicts that gains from DTCA, M&E and detailing all would come largely from competing drugs.

1. Introduction

An important decision made by brand managers is the choice of the marketing mix to help accomplish the sales and market share goals of the brand. Available marketing instruments differ by industry, but typically include prices, advertising, trade promotions, consumer promotions such as coupons and sweepstakes, in-store merchandising, and sales force efforts, as well as longer-term choices such as product-line depth and breadth. Since different instruments affect consumer behavior in different ways, the brand manager has the responsibility of mixing the marketing instruments optimally to achieve the brand's goals. This may require, for instance, that in early stages of the product life cycle, a brand places emphasis on category expanding activities while in later, more mature stages of the life cycle, emphasis is placed on stealing share from competitors.

Some marketing activities expand overall category demand by encouraging new purchases in the category, while others lead to stealing from competing brands. To illustrate using advertising as an instrument, the "Got Milk" campaign is clearly intended to grow primary demand for the category, milk. Similarly, a campaign that encourages use of a brand in a situation typically associated with a different category is intended to draw new category buyers to the brand (Wansink 1994). By contrast, comparative advertising that persuades the consumer about superiority of a brand's features over a competing brand is aimed at encouraging within-category brand switching. Temporary reductions in the price of a brand on the retail shelf typically have a similar brand switching goal. Nijs, Dekimpe et al. (2001) reports that such price promotions rarely have persistent category expanding effects, while new product introductions do expand the category.

An important implication of the choice of marketing mix by a given brand is the impact on competing brands' sales and market share -- some marketing actions are more threatening to competitors than others. At one extreme, marketing actions that primarily grow the category by attracting new buyers may even benefit competitors' sales. On the other hand, actions that primarily induce buyers to switch from competing brands in the category clearly 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 reaction. Leeflang and Wittink (2001) find empirically that managers' competitive reactions do take into account consumer response; the greater the cross-brand demand elasticity, the greater the competitive reaction elasticity. Steenkamp, Nijs 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 are sales gains from price promotions. Considerations of likely competitive response naturally affect the manager's choice of the optimal marketing mix.

To help the brand manager make informed marketing mix decisions, it is essential that marketing mix models appropriately measure the different effects of marketing instruments. The key argument of this paper is that extant discrete choice models are restrictive in this regard and can in fact misinform and misguide the manager. Classical models such as the logit, nested logit, and probit model make it appear that all marketing instruments are identical in terms of the source of share gains (Steenburgh 2008),

whereas our previous examples have illustrated that in fact differences between instruments could be substantial.

Discrete choice models are commonly used to analyze how consumers respond to marketing actions in terms of whether or not to buy (purchase incidence) and which brand to buy (brand choice) (Bucklin, Gupta et al. 1998; Bell, Chiang et al. 1999). Thus, these models allow measurement of the proportion of increase in a brand's choice share due to a given marketing action that is attributable to market expansion versus brand switching. Recent work, however, shows that a large class of existing discrete choice models, including ones that have been used to address this problem, possess the Invariant Proportion of Substitution (IPS) property, which implies that the proportion of demand generated by substitution away from a given competing alternative is the same, no matter which marketing instrument is employed (Steenburgh 2008). This is troubling because it implies that the proportion of growth due to new consumers purchasing in the category is the same no matter which marketing action is taken.

Following Steenburgh (2008), we propose an alternative choice model specification that relaxes the IPS property – the Flexible Substitution Logit (FSL) model – and allows a wider variety of substitution patterns to be found in the data. We find that the FSL model provides a better fit to the data than extant models, and its conclusions vary substantially as well. Furthermore, we show that the FSL allows greater agreement between individual and population substitution patterns than extant models because it imposes neither IIA nor IPS on individual choice behavior.

We demonstrate our arguments empirically in the context of the marketing of prescription drugs, a context in which these issues are of central concern not only for brand managers but also for public policy makers. We show that patient-directed marketing instruments such as Direct to Consumer Advertising (DTCA) often work quite differently than physician-directed marketing actions such as detailing in terms of sources of demand gains. As a result, we might expect that models that possess the IPS property will provide an overly restricted representation of the effects of these activities. Indeed, our empirical application to prescription writing choices of physicians in the hyperlipidemia category shows this to be the case.

We find that three commonly used models that all suffer from the IPS restriction -- the homogeneous logit model, the nested logit model, and the random coefficient logit model – lead to counter-intuitive estimates of the sources of demand gains due to increased marketing investments in DTCA, detailing, and professional Meetings and Events (M&E). The same is not true for the FSL. In particular, the FSL model provides the important insight that while most of the gains from detailing investments come at the expense of competing brands in the category (84%), most of the gains from DTCA and M&E are realized from patients who are not prescribed any drug treatment (87.4% and 70.2% respectively). In other words, competitor brands should be much less threatened by DTCA and M&E actions than by detailing. This key distinction in how the marketing instruments work is disguised by extant models.

The rest of this paper is organized as follows. In Section 2 we describe the data. In Section 3 we present specifications of extant models as well as the FSL model. In Section

4 we discuss results of our empirical analysis. Section 5 concludes with a discussion of results and implications for managerial actions and future research.

2. Data

We have chosen to examine differences in share stealing across marketing instruments in the context of pharmaceutical marketing. While there are multiple constituencies that determine demand for a brand drug, pharmaceutical firms in the US devote most of their marketing resources primarily to influence two groups -- physicians and patients. 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 DTCA, and $3.4 billion to M&E (CBO 2009).

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 pharmaceutical firms' representatives. The representatives inform physicians about drug efficacy and safety, answer physicians' questions, and establish and maintain goodwill of the brand. During the detailing visits, sales representatives also provide physicians with drug samples. Firms have full control on what to communicate with physicians as long as messages conform to FDA regulations and these communications take place behind closed doors.

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 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 like medical education communication companies or professional societies. 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 direct-to-consumer advertising. 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 be able to 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 and this 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 "non-drug prescriptions." The latter is a source that expands the category.

As discussed above, in the pharmaceutical industry, various marketing instruments are employed by firms and they are expected to influence demand, and hence competition, quite differently.

The therapeutical class that we use in this study is statins (or HMG-CoA reductase inhibitors). Statins are drugs used to lower cholesterol levels in people at risk for cardiovascular disease because of hyperlipidemia. Statins are the most potent anti-hyperlipidemia agents and have dominated the anti- hyperlipidemia market. Statins sales surpassed $14.3 billion in 2009, making them one of the biggest selling drugs in the United States[1]. During the period spanned by our data (2002–2004), there are four major statins available for prescription: Lipitor produced by Pfizer, Zocor by Merk, Pravachol by Bristol-Myers Squibb (BMS) and Crestor by AstraZeneca. "Non-drug only treatment" is also a common prescription issued by physicians if patients' diagnosed condition is not severe enough for drug treatment. Non-drug treatment methods include: eating healthy, 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 from a sample of 247 physicians in the U.S. over a 24-month period, from 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 US, balanced across geographic regions, physician specialties and prescription volumes. Data on monthly DTCA

[1] Source: IMS National Prescription Audit PLUS.

expenditures come from Kantar Media Intelligence. We link each patient visit to Designated Media Area (DMA) level DTCA expenditures through physician-level zip codes. DTCA is measured as $ expenditure per capita based on the population of the DMA.

In Table 1 we present summary statistics of the data. Taking the unit of analysis to be physician-month for each of the four brands and for non-drug treatment, we show the number of prescriptions and market share of prescriptions, and levels of each of the marketing mix instruments. As shown in Table 1, 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. The prescription shares show that about one quarter of visits receives prescription for non-drug treatment instead of a drug treatment. Among the four drugs, Lipitor is the market leader, followed by Crestor, Zocor, and Pravachol.

_____Table 1 about here_____

The impacts of marketing variables considered in this study are 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 introduce a vector of stock variables for marketing instruments:

$$x_{pjt} = \lambda x_{pjt-1} + \{DET_{pjt}, ME_{pjt}, DTC_{pjt}\}$$

where DET_{pjt} is the number of detailing visits by drug j to physician p in month t; ME_{pjt} is the number of M&E sponsored by drug j that received participation by

physician p in month t; DTC_{pjt} is drug j's DTCA per capita $ expenditure in physician p's DMA area in month t; λ is the carry-over parameter with a value between 0 to 1.

For simplicity, we fixed the carry-over parameters of detailing and M&E at 0.86 each, and that of DTCA at 0.75, based on previous research (Narayanan, Desiraju et al. 2004). We use the first 14 months of data to calculate the value of initial stock of each marketing instrument. All models are fitted on the remaining 10 months of data.

3. Model Specification

In this section, we discuss the types of restrictions that two major discrete choice models -- the logit and the nested logit -- impose on individual substitution patterns. We then propose a model that allows for greater flexibility in substitution patterns. We also discuss the type of flexibility that taste heterogeneity adds to these models.

3.1 Logit

The most basic choice model is the homogeneous multinomial logit (McFadden 1974). This model is constructed by decomposing the decision maker's utility into observed and unobserved components, such that

$$u_j = v_j + \varepsilon_j$$

The observed utility for alternative j, v_j is a function of observed attributes, x_j, and the decision maker's preferences, β. Typically, the observed utility of alternative good j is specified as a linear function, such that $v_j = x_j\beta$ and the observed utility of the outside good is defined to be zero ($v_0 = 0$). The unobserved utility, ε_j, is assumed to follow an independent and identically distributed extreme value distribution.

Given these assumptions, the probability that the decision maker chooses alternative j is

$$P_j = \begin{cases} e^{x_j\beta} \Big/ (1+\sum_{l=1}^{J} e^{x_l\beta}) & j \neq 0 \\ 1 \Big/ (1+\sum_{l=1}^{J} e^{x_l\beta}) & j = 0 \end{cases}$$

As is well known, these choice probabilities mean that the homogeneous logit suffers from the Independence of Irrelevant Alternatives (IIA) property, an undesirable assumption about how decision makers substitute among alternatives. Specifically, IIA implies that demand must be drawn from competing alternatives in proportion to their market shares. For example, suppose the market share of Lipitor is 25%, Zocor is 15%, Pravachol is 10%, Crestor is 20% and the non-drug treatment is 30%. If an incremental marketing investment yields 100 additional units for Lipitor, then IIA implies that 20% of those units must come from Zocor, 13% from Pravachol, 27% Crestor, and 40% from the non-drug treatment.

The homogeneous logit model also suffers from the Invariant Proportion of Substitution (IPS) property (Steenburgh 2008), another undesirable assumption about how decision makers substitute among alternatives. The proportion of incremental demand for alternative j drawn from alternative good *k* for a change in any attribute x_{ja} is

$$\frac{-\partial P_k / \partial x_{ja}}{\partial P_j / \partial x_{ja}} = \frac{P_k}{1-P_j} \quad k = 0,1 \cdots J, \quad j \neq 0$$

Since the logit model has IPS, this ratio does not depend on which attribute is changed. In other words, regardless of whether the brand manager invests in detailing, M&E or

DTCA, the incremental demand for Lipitor must be drawn from the competing alternatives in the same proportion.

The IPS property is especially troubling in our context because the point of the study is to determine whether specific marketing investments steal demand from competing drugs or from the non-drug treatment. We might expect detailing to draw a greater proportion of demand from competing goods than M&E and DTCA do. The logit would not let us find this out because it requires demand to be drawn from each competing alternative in proportion to its market share. Returning to the example, the model requires 60% of the incremental demand to be drawn from competing drugs and 40% to be drawn from the non-drug treatment no matter which investment is made.

3.2 Nested Logit

Given that the logit model assumes overly restrictive substitution patterns, many new choice models have been proposed to allow greater flexibility. The nested logit (Ben-Akiva 1973; McFadden 1978; Williams 1997), one of the more prominent models, has been used in previous decomposition studies (Bucklin, Gupta et al. 1998; Bell, Chiang et al. 1999). It is a step forward because it does not require demand to be drawn from competing alternatives in proportion to their market share.

The nested logit is derived by creating a nesting structure on unobserved attributes. Let the choice set be grouped into N non-overlapping subsets denoted by $B_1, B_2, \ldots, B_N$. The utility that a decision maker derives from choosing alternative *j* in nest B_n is specified as

$$u_j = v_j + \varepsilon_j$$

The nested logit model is derived by assuming the unobserved utility, ε, has cumulative distribution

$$\exp(-\sum_{n=1}^{N}(\sum_{j\in B_n} e^{-\varepsilon_j/(1-\rho_n)})^{1-\rho_n})$$

where $0 \le \rho_n < 1$ denotes the correlation among alternatives in nest B_n.

Given these assumptions, the probability that the decision maker chooses alternative $j \in B_n$ is

$$P_j = P_{B_n} \cdot P_{j|B_n},$$

where

$$P_{B_n} = \frac{e^{(1-\rho_n)I_n}}{\sum_{l=1}^{N} e^{(1-\rho_l)I_l}},$$
$$I_l = \ln \sum_{i\in B_l} e^{v_i/(1-\rho_l)},$$
$$P_{j|B_n} = \frac{e^{v_j/(1-\rho_n)}}{\sum_{i\in B_n} e^{v_i/(1-\rho_n)}}.$$

$P_{j|B_n}$ is the probability of choosing alternative j given nest B_n is chosen; P_{B_n} is the probability of choosing nest B_n; and I_n is the inclusive value of nest B_n.

We want to allow more flexible substitution between the four drugs brands and the non-drug treatment. Following the work of Bucklin, Gupta et al. (1998) and Bell, Chiang, et al (1999), we divide the choice alternatives into two nests: one (B_0) containing the non-drug treatment and the other (B_1) containing the four drug brands. Given these assumptions, the probability that the physician prescribes non-drug treatment only is

$$P_0 = \frac{1}{1+(\sum_{i\in B_1} e^{V_i/(1-\rho_1)})^{(1-\rho_1)}}$$

and the probability of prescribing drug j is

$$P_j = \frac{e^{V_j/(1-\rho_1)}\left(\sum_{j\in B_1} e^{V_j/(1-\rho_1)}\right)^{-\rho_1}}{1+\left(\sum_{i\in B_1} e^{V_i/(1-\rho_1)}\right)^{(1-\rho_1)}} \quad for\ \ j \in B_1$$

The substitution ratio is given as the following,

$$\frac{-\partial P_k/\partial x_{ja}}{\partial P_j/\partial x_{ja}} = \begin{cases} \dfrac{P_k[\rho_1 P_{j|B_1} + (1-\rho_1)P_j]}{P_j[1-\rho_1 P_{j|B_1} - (1-\rho_1)P_j]} & \text{for } k,\ j \in B_1 \\ \dfrac{P_0(1-\rho_1)}{1-\rho_1 P_{j|B_1} - (1-\rho_1)P_j} & k = 0 \text{ and } j \in B_1 \end{cases}$$

As can be seen in the substitution ratio, the nested logit does address concerns due to IIA. Demand is not drawn from the alternatives in proportion to their market. Returning to the example, the proportion of demand drawn from the non-drug treatment could be 80% even thought its market share is 40%.

Nevertheless, the nested logit does not address concerns due to IPS. The model implies that the proportion of demand drawn from a given competing alternative is the same no matter which marketing investment is made. If the model predicts that 80% of the demand comes from the non-drug alternative following an investment in DTCA, then it will predict the same 80% following investments in M&E and detailing. Given the question that we are asking, we would like to develop a more flexible model.

3.3 Flexible Substitution Logit (FSL)

We have focused on the logit and nested logit models because they have been used in previous decomposition studies, but many other choice models possess the IPS property too. This class of models includes all generalized extreme value and the covariance probit models. Therefore, we have to develop a new choice model to address this problem.

Steenburgh (2008) suggests that it might be useful to relax the IPS property in the context of this problem by allowing the utility function of a given alternative to depend not only on its own attributes, but also on the attributes of competing alternatives. This means that investments in DTCA made by Lipitor should enter not only the utility function of Lipitor, but also the utility functions of Zocor, Pravachol, and Crestor. We propose a model based on this idea, called the flexible substitution logit (FSL). Unlike the logit or nested logit models, it allows the substitution patterns to vary across marketing instruments.

The FSL model is derived as follows. The utility that a physician derives from prescribing alternative *j* is

$$u_j = v_j + \varepsilon_j$$

But the observed utility of good *j* depends on the attributes of all goods, such that

$$v_j = x_j \beta + \left(\sum_{i=1}^{J} x_i \right) \gamma$$

and the observed utility of the outside good is defined to be zero. In effect, this specification creates a nesting structure on observed attributes. Marketing action x_{ja} has two effects on the focal drug:

(1) It increases preference for the focal drug over competing drugs in the category by β_a.

(2) It increases preference for the focal drug over the non-drug treatment by $\beta_a + \gamma_a$.

In addition to its effect on the focal drug, the marketing action increases preference for the competing drugs over the non-drug treatment by γ_a. The FSL is a form of the

universal logit (McFadden 1975; Koppelman and Sethi 2000) because it allows the attributes of competing alternatives to enter the utility function of the focal drug. If $\gamma = 0$, then the FSL collapses to the logit model[2].

If we assume that ε_j are distributed extreme value, then the probability that the decision maker chooses alternative j is

$$P_j = \frac{\exp\left(x_j\beta + \left(\sum_{i=1}^{J} x_i \right)\gamma \right)}{1 + \sum_{l=1}^{J} \exp\left(x_l\beta + \left(\sum_{i=1}^{J} x_i \right)\gamma \right)}$$

Since the choice probabilities take a closed form, the FSL is easy to estimate with standard programs.

The proportions of demand drawn from the competing drugs and the non-drug treatment are

$$\frac{-\partial P_k / \partial x_{ja}}{\partial P_j / \partial x_{ja}} = \begin{cases} \dfrac{P_k P_j \beta_a - P_k P_0 \gamma_a}{P_j\left(1-P_j\right)\beta_a + P_j P_0 \gamma_a} & \text{for } k \neq 0,\ j \neq 0 \\ \dfrac{P_0 P_j \beta_a + P_0\left(1-P_0\right)\gamma_a}{P_j\left(1-P_j\right)\beta_a + P_j P_0 \gamma_a} & \text{for } k = 0,\ j \neq 0 \end{cases}$$

(Proof is provided in the appendix.) Unlike either of the previous models, the FSL allows the proportion of demand drawn from both competing drugs and the non-drug alternative to vary across marketing instruments. (The flexibility is achieved because β_a and γ_a can vary across marketing instruments.) For example, 80% of the incremental demand could be created by market expansion if the brand manager were to invest in DTCA, but only 15% of the incremental demand could be created by market expansion

[2] The universal logit has not been used much in practice. A notable exception is Krishnamurthi et al. (1995).

if the manager were to invest in detailing. It seems reasonable to allow for this possibility given our prior expectations of how the two marketing instruments work.

3.4 Flexibility Provided by Taste Heterogeneity

Heterogeneous choice models allow a wider variety of substitution patterns to occur among market shares than their homogeneous counterparts do. This does not mean, however, that allowing for taste variation solves the problems associated with IIA and IPS. Adding taste heterogeneity to a choice model does not change individual substitution patterns, and models such as the random coefficient logit and random coefficient nested logit preclude individual choice behavior that is reasonable (Steenburgh, 2008). In contrast, the FSL allows a wider variety of individual-level choice behavior to be recovered from the data.

We create heterogeneous versions of all three models through random coefficients specifications. For example, the random coefficients FSL is specified as

$$U_{ij} = X_j \beta_i + \varepsilon_{ij}$$

where

$$\beta_i \sim N(\beta, \Sigma)$$

Since the random coefficients FSL nests the random coefficients logit, we can empirically test whether adding flexibility at the individual-level of the model matters. Furthermore, we will use the estimates to compare the substitution patterns of all three models at both the individual and population levels, showing that the patterns of the FSL are logically consistent at both levels.

4. Results

To begin with we assumed parameter homogeneity across physicians and estimated a standard logit, a nested logit, and a FSL model. We then incorporated physician heterogeneity and estimated a random coefficient logit, a random coefficient nested logit, and a random coefficient FSL model on the data.

4.1 Homogeneous Case

Parameter estimates and model fit statistics of the three homogeneous models are presented in Table 2. Both AIC and BIC indicate that the FSL model fits the data best, followed by the nested logit model and then the logit.

_____Table 2 about here_____

In Table 3, we present the own elasticities for Lipitor (as an illustration) and the substitution matrices. All the models find positive effects of detailing, DTCA, and M&E on physicians' probability of prescribing the marketed drug. Notice that each model comes to roughly the same conclusion about the ability of marketing instruments to generate demand. The elasticity of demand is greatest from detailing (the own-elasticity is 0.225 in the logit, 0.250 in the nested logit, and 0.269 in the FSL model). This is followed by the elasticity of demand from DTCA (0.122 in the logit, 0.102 in the nested logit, and 0.095 in the FSL). The elasticity of demand is smallest from M&E (0.037 in the logit, 0.037 in the nested logit, and 0.035 in the FSL).

_____Table 3 about here_____

Although the models come to roughly the same conclusion about the ability of the marketing instruments to generate demand, they predict very different substitution

patterns among the drugs. Let us begin by discussing the substitution patterns imposed by the logit model. Due to the IIA property, the logit model predicts that demand will be drawn from each of the alternatives in proportion to their market share. Thus, for every marketing instrument, the logit model implies that 67.1% of the incremental demand for Lipitor is drawn from competing drugs (20.7% from Zocor , 14.4% from Pravachol, and 32.0% from Crestor) and 32.9% is drawn from the non-drug treatment. This approach to decomposition is consistent with the unit-based decomposition proposed by van Heerde, Gupta et al. (2003) and Steenburgh (2007). By comparison, the market shares in the raw data, excluding Lipitor, are 21.0% for Zocor, 14.7% for Pravachol, 31.9% for Crestor and 32.4% for the non-drug treatment.

The logit model imposes overly restrictive substitution patterns on the data. First, there is no reason to believe that demand will be drawn from the competing alternatives in proportion to their market share. Second, there is no reason to believe that the substitution patterns will be the same across the marketing instruments. The nested logit model has been used in many previous decomposition studies because it allows for more realistic substitution patterns to be found in the data. Although it cures the first problem because it does not require demand to be drawn from competing goods in proportion to their market shares, it does not cure the second problem which is due to the IPS property.

The nested logit model implies that the incremental demand for Lipitor will be disproportionately (relative the actual market shares) drawn from competing drugs. Regardless of the marketing instrument being used, 78.2% of the incremental demand

for Lipitor is drawn from competing drugs (24.2% from Zocor, 16.9% from Pravachol, and 37.1% from Crestor) and only 21.8% is drawn from the non-drug treatment. The nested logit model is more flexible than the logit because it allows for a wider variety of substitution patterns. Yet, it seems to be inadequate for the question that we are asking because of the IPS property. There is no reason to believe that the proportion of demand created by market expansion is the same for detailing, DCTA and M&E.

The FSL model allows a much richer set of substitution patterns to be recovered from the data because it is not subject to the IPS property. Most of the incremental demand created by detailing, 84.0%, is stolen from competing drugs (26.2% from Zocor, 18.3% from Pravachol, and 39.5% from Crestor) and only 16.0% is drawn from the non-drug treatment. These results suggest that salespeople may be selling the benefits of Lipitor against the benefits of competing drugs behind the closed doors of a doctor's office.

In stark contrast, the opposite occurs with the other marketing instruments. Most of the incremental demand created by DTCA, 87.4%, is drawn the non-drug treatment, with only 12.6% being drawn from the competing drugs (3.8% from Zocor, 2.7% from Pravachol, and 5.8% from Crestor). Similarly, most of the incremental demand created by M&E, 70.2%, is drawn the non-drug treatment, with only 29.8% being drawn from the competing drugs (9.3% from Zocor, 6.5% from Pravachol, and 14.0% from Crestor). These results suggest that DTCA and M&E have spillover effects not found in detailing.

This seems to make sense because some pharmaceutical advertisements create awareness of a drug option and may also generate patient requests for medication.

Donohue, Berndt et al.(2004) 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. Furthermore, meetings and events are disease oriented communications in nature and allow physicians to speak to one another, which may make the drug companies less willing to draw comparisons between the drugs.

These results have important managerial implications too. Suppose a brand manager is trying to decide whether to invest their marketing dollars in detailing or DTCA. An investment in detailing will lead to a greater immediate increase in demand. The model implies that a 10% increase in the level of detailing will yield a 2.69% increase in demand, whereas a 10% increase in the level of DTCA will yield only a .95% increase in demand. Given these numbers, it seems like we would much rather invest in detailing than in DTCA.

Nevertheless, 84.0% of the demand created by detailing is stolen from competing drugs, meaning that the demand for Lipitor increases by 2.26% by stealing demand away from other drugs and 0.43% comes at the expense of the non-drug option. By comparison, 87.4% of the demand created by DTCA comes from the non-drug option. This means that the demand for Lipitor increases by 0.12% by stealing demand away from other brands and .83% comes at the expense of the non-drug option. Thus, it would seem that competing drugs would have a greater incentive to retaliate if the Lipitor brand manager invests in detailing than if she invests in DTCA. Analogously, the

increase in demand that comes at the expense of non-drug treatment is greater if the manager invests in DTCA than if she invests in detailing.

4.2 Heterogeneous Case

Although the FSL is the most flexible of the three homogeneous models we considered, we may wonder whether allowing for heterogeneity across physicians increases the flexibility of the logit and nested logit models and allows them to recover more realistic substitution patterns. To answer this empirical question we estimate heterogeneous versions of the three previously presented models – a random coefficient logit, a random coefficient nested logit, and a random coefficient FSL model. Estimation results are presented in Tables 4 – 6. In all models, we find evidence of significant heterogeneity across physicians in their responsiveness to marketing instruments. Furthermore, we find that the random coefficient FSL fits the data best, followed by the random coefficient logit, and then the random coefficient nested logit.

_____Tables 4, 5, and 6 about here_____

In Table 7, we present the own elasiticities for Lipitor (as an illustration) and the substitution matrices. All three models imply that detailing, DTCA, and M&E have positive effects on a physician's probability of prescribing the marketed drug. Notice that all three models come to roughly the same conclusion about the ability of the marketing instruments to generate demand for Lipitor. The elasticity of demand is greatest for detailing (the own-elasticity is 0.329 in the random coefficient logit, 0.317 in the random coefficient nested logit, and 0.291 in the random coefficient FSL). The elasticities of

demand for DTCA and M&E are quite close in magnitude in each of the three models, and both are considerably smaller than the elasticity for detailing.

_____Table 7 about here_____

Nevertheless, the models again come to very different conclusions about the substitution patterns among drugs. Unlike the homogeneous case, the random coefficient logit does allow for some variation in the substitution patterns across marketing instruments. The proportion of demand drawn from the non-drug treatment is 25.0% from detailing, 36.6% from DTCA, 36.4% from M&E. Similarly, the random coefficient nested logit implies that the proportion of demand drawn from the non-drug treatment is 15.2% from detailing, 27.0% from DTCA, and 27.0% from M&E. The direction of these results is consistent with what we found with the homogeneous FSL model. The proportion of demand that is stolen from competing drugs is greater for detailing than it is for DTCA and M&E. The magnitude of these differences, however, is much smaller, suggesting that the model is not as flexible as might be desired.

In contrast, the random coefficient FSL allows a richer set of substitution patterns to be recovered from the data. As we found in the homogeneous case, most of the incremental demand created by detailing, 79.0%, 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 non-drug treatment, 75.9% and 59.1% respectively. Allowing for heterogeneity provides only a limited degree of flexibility. Depending on the question being addressed, it may be more important to allow for flexibility across marketing instruments than across individuals.

We explore this issue further by examining the flexibility allowed and restrictions imposed by the models on individual physicians. In Tables 8a and 8b, we report the own elasticities and the substitution patterns for two systematically selected physicians in our data set. The random coefficient logit and random coefficient nested logit do provide more flexibility than their homogeneous counterparts because they allow the own elasticites to vary across physicians. For example, the random coefficient (nested) logit implies that the own elasticity from detailing is 0.204 (0.177) for physician A and 0.488 (0.264) for physician B. Furthermore, these models allow the substitution patterns to vary across physicians. The random coefficient (nested) logit implies that 28.3% (21.2%) of the incremental likelihood of Physician A prescribing Lipitor is drawn from the non-drug alternative whereas Physician B draws 38.1% (27.4%) from the non-drug treatment.

_____Tables 8a and 8b about here_____

Nevertheless, both the random coefficient logit and the random coefficient nested logit impose the IPS property on individual physicians' choice behavior. This means that the substitution patterns for a given physician *must* be the same across marketing instruments. For example, regardless of the instrument being used, the random coefficient (nested) logit implies that 71.7% (78.8%) of the incremental demand for Lipitor attributable to physician A is drawn from competing drugs and 28.3% (21.2%) from the non-drug treatment. Yet, there is no reason to believe that the Physician A will behave the same way regardless of the marketing investment being made. The same pattern can be seen in Physician B's choice behavior. Given that the focus of the study is to make statements about differences in the substitution patterns across marketing

instruments, it seems especially hard to justify requiring them to be the same at the individual level.

In contrast, the random coefficient FSL allows the substitution patterns to vary across marketing instruments at both the individual and aggregate levels. For example, the random coefficient FSL model implies that Physician A substitutes among the drugs in different ways depending on the marketing action being taken. Most of the incremental demand for Lipitor, 72.7%, is drawn from the competing drugs when detailing is used. Yet, most of the demand is drawn from the non-drug treatment when the other marketing instruments are used, 73.7% for DTCA and 71.0% for M&E. Unlike the other models, the random coefficient FSL can recover more realistic substitution patterns at both levels of the model.

5. Discussion, Conclusions, and Future Research

An essential decision facing any brand manager is the choice of marketing instruments to enhance the 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, the nested logit, and the probit have been used to analyze how consumers respond to marketing actions in terms of whether or not to buy (purchase incidence) and which brand to buy (brand choice). However, these models possess the IPS property. The IPS property implies that the proportion of demand generated by substitution away from a given competing alternative is the same, no matter which marketing instrument is employed. Indeed our empirical application to prescription writing choices of physicians in the hyperlipidemia market shows this to be

the case. We find that three commonly used models that all suffer from the IPS restriction – the homogeneous logit model, the nested logit model, and the random coefficient logit model – lead to counter-intuitive estimates of the sources of demand gains due to increased marketing investments in DTCA, detailing, and meetings and events.

We then employ an alternative choice model specification that relaxes the IPS property – the flexible substitution logit (FSL) model. The FSL model, both homogeneous and random coefficient forms, predicts that increases in DTCA and M&E result in sales gains that come primarily from non-drug treatments rather than from other cholesterol lowering drugs. By contrast, the random coefficient logit model predicts for all three marketing instruments – DTCA, detailing, and M&E – that gains would come largely at the expense of competing drugs. This empirical result also suggests that the IPS property cannot be relaxed by adding physician heterogeneity.

With the proposed FSL model, a brand manager of prescription drugs can 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 like DTCA or M&E if retaliation by competing brands is a significant concern. We believe there is considerable room for future research in this area. For instance, it would be important to identify other contexts in which the IPS property has important implications. Similarly, alternative models that overcome IPS should also be explored.

Table 1: Summary Statistics

Unit of analysis is physician-month. N=5928

Number of Prescriptions	Brand	Mean	Std Dev	Share of prescriptions
	Lipitor	0.557	1.177	0.287
	Zocor	0.291	0.620	0.150
	Pravachol	0.203	0.704	0.105
	Crestor	0.442	1.415	0.228
	Non-drug Treatment	0.448	1.076	0.231
Marketing Instrument				
Detailing	Lipitor	0.634	1.035	
(number of visits)	Zocor	0.728	1.128	
	Pravachol	0.366	0.746	
	Crestor	0.960	1.316	
DTCA	Lipitor	0.040	0.016	
($ per capita)	Zocor	0.028	0.009	
	Pravachol	0.008	0.009	
	Crestor	0.023	0.039	
M&E	Lipitor	0.031	0.202	
(number of meetings & events)	Zocor	0.006	0.079	
	Pravachol	0.004	0.064	
	Crestor	0.047	0.227	

Table 2: Maximum Likelihood Parameter Estimates and Fit Statistics of Three Homogeneous Models (Standard errors in parentheses)

Variables	Logit	Nested Logit	Universal Logit
Intercept of Lipitor	-0.405	0.146	-0.402
	(0.060)	(0.168)	(0.087)
Intercept of Zocor	-0.963	-0.213	-0.993
	(0.059)	(0.222)	(0.089)
Intercept of Pravachol	-1.071	-0.272	-1.084
	(0.055)	(0.232)	(0.094)
Intercept of Crestor	-0.433	0.128	-0.456
	(0.047)	(0.168)	(0.088)
Own - detailing - stock	0.072	0.053	0.092
	(0.005)	(0.008)	(0.006)
Own - DTCA - stock	4.247	2.341	2.577
	(1.092)	(0.890)	(1.197)
Own - M&E - stock	0.300	0.194	0.241
	(0.034)	(0.039)	(0.035)
Total-detailing-stock			-0.018
			(0.003)
Total-DTCA-stock			2.328
			(0.917)
Total-M&E-stock			0.136
			(0.038)
Inclusive value		0.635	
		(0.102)	
Log likelihood	-7761	-7756	-7735
AIC	15536	15528	15490
BIC	15582	15580	15555

Table 3: Substitution Matrices and Own Elasticities (for Lipitor) for the Three Homogeneous Models

	Logit Model			Nested Logit Model			FSL		
	Detailing	DTCA	M&E	Detailing	DTCA	M&E	Detailing	DTCA	M&E
Lipitor	-	-	-	-	-	-	-	-	-
Zocor	20.7%	20.7%	20.7%	24.2%	24.2%	24.2%	26.2%	3.8%	9.3%
Pravachol	14.4	14.4	14.4	16.8	16.8	16.8	18.3	2.7	6.5
Crestor	32.0	32.0	32.0	37.1	37.1	37.1	39.5	5.8	14.0
Nondrug Treatment	32.9	32.9	32.9	21.8	21.8	21.8	16.0	87.4	70.2
Total	100	100	100	100	100	100	100	100	100
Own Elasticity	0.225	0.122	0.037	0.250	0.102	0.037	0.269	0.095	0.035

For each model, cell entries in each column indicate the percentage of sales increase of Lipitor due to a 1% increase in its marketing instrument (e.g. detailing) that is drawn from the alternative indicated in the row. For example, the logit model predicts that if Lipitor increases its detailing by 1%, 20.7% of its incremental sales will come from Zocor.

Table 4: Parameter Estimates of Random coefficient Logit Model

Variables	Mean	Interval (95%)	Standard Deviation	Numerical Standard Error
Intercept of Lipitor	-0.304	-0.486, -0.135	0.087	0.007
Intercept of Zocor	-1.297	-1.549, -1.102	0.111	0.009
Intercept of Pravachol	-1.842	-2.124, -1.543	0.149	0.012
Intercept of Crestor	-1.010	-1.250, - 0.784	0.118	0.006
Own - detailing - stock	0.129	0.105, 0.154	0.013	0.001
Own - DTCA - stock	0.836	0.432, 1.162	0.219	0.026
Own - M&E - stock	0.263	0.223, 0.315	0.027	0.003
Log of Integrated Likelihood	-5910			

Table 5: Parameter Estimates of Random coefficient Nested Logit Model

Variables	Mean	Interval (95%)	Standard Deviation	Numerical Standard Error
Intercept of Lipitor	0.152	0.005, 0.274	0.069	0.006
Intercept of Zocor	-0.500	-0.693, -0.332	0.093	0.009
Intercept of Pravachol	-0.784	-1.058, -0.584	0.125	0.012
Intercept of Crestor	-0.296	-0.541, - 0.080	0.121	0.011
Own - detailing - stock	0.086	0.067, 0.106	0.010	0.001
Own - DTCA - stock	1.960	1.684, 2.214	0.140	0.016
Own - M&E - stock	0.239	0.132, 0.352	0.061	0.007
Inclusive Value	0.669	0.628, 0.704	0.019	0.002
Log of Integrated Likelihood	-5965			

Table 6: Parameter Estimates of Random coefficient FSL Model

Variables	Mean	Interval (95%)	Standard Deviation	Numerical Standard Error
Intercept of Lipitor	-0.339	-0.499, -0.193	0.080	0.007
Intercept of Zocor	-1.330	-1.619, -1.055	0.153	0.016
Intercept of Pravachol	-1.672	-1.913, -1.430	0.125	0.009
Intercept of Crestor	-1.023	-1.271, -0.769	0.130	0.009
Own - detailing – stock	0.111	0.082, 0.151	0.019	0.002
Own - DTCA – stock	1.414	1.171, 1.696	0.157	0.018
Own - M&E - stock	0.308	0.272, 0.354	0.020	0.002
Total-detailing-stock*	-	-	-	-
Total-DTCA-stock	1.063	0.723, 1.534	0.226	0.027
Total-M&E-stock	0.129	0.097, 0.166	0.019	0.002
Log of Integrated Likelihood	-5886			

* The effect of total-detailing-stock is not significant and therefore removed from the model.

Table 7: Substitution Matrices and Own Elasticities (for Lipitor) for Random coefficient Logit, Random coefficient Nested Logit and Random coefficient FSL Models

	Random coefficient Logit Model			Random coefficient Nested Logit Model			Random coefficient FSL		
	Detailing	DTCA	M&E	Detailing	DTCA	M&E	Detailing	DTCA	M&E
Lipitor	-	-	-	-	-	-	-	-	-
Zocor	29.5%	23.7%	23.7%	34.0%	27.2%	26.7%	30.0%	8.8%	14.8%
Pravachol	14.9	13.8	13.8	15.7	16.0	16.0	16.2	5.3	9.3
Crestor	30.6	25.9	26.2	35.1	29.8	30.3	32.8	9.9	16.8
Non-drug Treatment	25.0	36.6	36.4	15.2	27.0	27.0	21.0	75.9	59.1
Total	100	100	100	100	100	100	100	100	100
Own Elasticity	0.329	0.019	0.026	0.317	0.061	0.032	0.291	0.041	0.035

Table 8a: Substitution Matrices for Random coefficient Logit, Random coefficient Nested Logit and Random coefficient FSL – Physician A who is relatively insensitive to detailing

	Random coefficient Logit Model			Random coefficient Nested Logit Model			Random coefficient FSL		
	Detailing	DTCA	M&E	Detailing	DTCA	M&E	Detailing	DTCA	M&E
Lipitor	-	-	-	-	-	-	-	-	-
Zocor	24.0%	24.0%	24.0%	29.5%	29.5%	29.5%	23.9%	8.7%	9.6%
Pravachol	18.1	18.1	18.1	19.8	19.8	19.8	19.5	7.1	7.8
Crestor	31.6	31.6	31.6	29.5	29.5	29.5	29.2	10.6	11.7
Non-drug Treatment	28.3	28.3	28.3	21.2	21.2	21.2	27.3	73.7	71.0
Total	100	100	100	100	100	100	100	100	100
Own Elasticity	0.204	0.025	0.027	0.177	0.074	0.045	0.136	0.050	0.050

Table 8b: Substitution Matrices for Random coefficient Logit, Random coefficient Nested Logit and Random coefficient FSL – Physician B who is more sensitive to detailing

	Random coefficient Logit Model			Random coefficient Nested Logit Model			Random coefficient FSL		
	Detailing	DTCA	M&E	Detailing	DTCA	M&E	Detailing	DTCA	M&E
Lipitor	-	-	-	-	-	-	-	-	-
Zocor	23.7%	23.7%	23.7%	33.6%	33.6%	33.6%	31.0%	16.6%	23.1%
Pravachol	4.8	4.8	4.8	6.8	6.8	6.8	3.9	2.1	2.9
Crestor	33.4	33.4	33.4	33.2	33.2	33.2	26.3	14.1	19.6
Non-drug Treatment	38.1	38.1	38.1	27.4	27.4	27.4	38.8	67.1	54.4
Total	100	100	100	100	100	100	100	100	100
Own Elasticity	0.488	0.018	0.033	0.264	0.051	0.027	0.251	0.037	0.031

Appendix

Proof:

$$P_j = \frac{\exp\left(x_j\beta + \left(\sum_{i=1}^{J} x_i \right)\gamma \right)}{1 + \sum_{l=1}^{J} \exp\left(x_l\beta + \left(\sum_{i=1}^{J} x_i \right)\gamma \right)}$$

$$\frac{\partial P_k}{\partial v_j} = \begin{cases} P_j\left(1 - P_j\right) & \text{for } k = j \\ P_j P_k & \text{for } k \neq j \end{cases}$$

$$\frac{\partial v_k}{\partial x_{ja}} = \begin{cases} \beta_a + \gamma_a & \text{for } k = j \\ \gamma_a & \text{for } k \neq j, 0 \\ 0 & \text{for } k = 0 \end{cases}$$

For k = j,

$$\begin{aligned} \frac{\partial P_j}{\partial x_{ja}} &= \sum_{l=1}^{J} \frac{\partial P_j}{\partial v_l} \cdot \frac{\partial v_l}{\partial x_{ja}} \\ &= \frac{\partial P_j}{\partial v_j} \cdot \frac{\partial v_j}{\partial x_{ja}} + \sum_{\substack{l=1 \\ l \neq j}}^{J} \frac{\partial P_j}{\partial v_l} \cdot \frac{\partial v_l}{\partial x_{ja}} \\ &= P_j\left(1 - P_j\right)\left(\beta_a + \gamma_a\right) - \sum_{\substack{l=1 \\ l \neq j}}^{J} P_j \cdot P_l \cdot \gamma_a \\ &= P_j\left(1 - P_j\right)\left(\beta_a + \gamma_a\right) - P_j\left(\sum_{\substack{l=1 \\ l \neq j}}^{J} P_l \right)\gamma_a \\ &= P_j\left(1 - P_j\right)\left(\beta_a + \gamma_a\right) - P_j\left(1 - P_j - P_0\right)\gamma_a \\ &= P_j\left(1 - P_j\right)\beta_a + P_j \cdot P_0 \cdot \gamma_a \end{aligned}$$

For k ≠ j, 0,

$$\begin{aligned}
\frac{\partial P_k}{\partial x_{ja}} &= \sum_{l=1}^{J} \frac{\partial P_k}{\partial v_l} \cdot \frac{\partial v_l}{\partial x_{ja}} \\
&= \frac{\partial P_k}{\partial v_j} \cdot \frac{\partial v_j}{\partial x_{ja}} + \frac{\partial P_k}{\partial v_k} \cdot \frac{\partial v_k}{\partial x_{ja}} + \sum_{\substack{l=1 \\ l \neq j,k}}^{J} \frac{\partial P_k}{\partial v_l} \cdot \frac{\partial v_l}{\partial x_{ja}} \\
&= -P_k P_j \left(\beta_a + \gamma_a\right) + P_k \left(1 - P_k\right) \gamma_a - \sum_{\substack{l=1 \\ l \neq j,k}}^{J} P_k P_l \gamma_a \\
&= -P_k P_j \left(\beta_a + \gamma_a\right) + P_k \left(1 - P_k\right) \gamma_a - P_k \left(1 - P_j - P_k - P_0\right) \gamma_a \\
&= -P_k P_j \left(\beta_a + \gamma_a\right) + P_k \left(P_j + P_0\right) \gamma_a \\
&= -P_k P_j \beta_a + P_k P_0 \gamma_a
\end{aligned}$$

For k=0,

$$\begin{aligned}
\frac{\partial P_0}{\partial x_{ja}} &= \sum_{l=1}^{J} \frac{\partial P_k}{\partial v_l} \cdot \frac{\partial v_l}{\partial x_{ja}} \\
&= \frac{\partial P_0}{\partial v_j} \cdot \frac{\partial v_j}{\partial x_{ja}} + \sum_{\substack{l=1 \\ l \neq j}}^{J} \frac{\partial P_0}{\partial v_l} \cdot \frac{\partial v_l}{\partial x_{ja}} \\
&= -P_0 P_j \left(\beta_a + \gamma_a\right) - \sum_{\substack{l=1 \\ l \neq j}}^{J} P_0 P_l \gamma_a \\
&= -P_0 P_j \left(\beta_a + \gamma_a\right) - P_0 \left(1 - P_j - P_0\right) \gamma_a \\
&= -P_0 P_j \beta_a - P_0 \left(1 - P_0\right) \gamma_a
\end{aligned}$$

The derivatives with respect to marketing actions x_{ja} are:

$$\partial P_k / \partial x_{ja} = \begin{cases} -P_k P_j \beta_a + P_k P_0 \gamma_a & \text{for } k \neq j, 0 \\ -P_0 P_j \beta_a - P_0 \left(1 - P_0\right) \gamma_a & \text{for } k = 0 \\ P_j \left(1 - P_j\right) \beta_a + P_j P_0 \gamma_a & \text{for } k = j \end{cases}$$

REFERENCES

Bell, D. R., J. Chiang, et al. (1999). "The Decomoposition of Promotional Response: An Empirical Generalization." Marketing Science **18**(4): 504-526.

Ben-Akiva, M. (1973). The structure of travel demand models. Department of Civil Engineering. Cambridge, MA, MIT Press. **PhD**.

Bucklin, R. E., S. Gupta, et al. (1998). "Determining Segmentation in Sales Response Across Consumer Purchase Behaviors." Journal of Marketing Research **35**(May): 189-197.

CBO (2009). Promotional Spending for Prescription Drugs. C. B. Office.

Donohue, J. M., E. R. Berndt, et al. (2004). "Effects of Pharmaceutical Promotion on Adherence to the Treatment Guidelines for Depression." Medical Care **42**(December): 1176-1185.

Koppelman, F. S. and V. Sethi (2000). Closed form discrete choice models. Handbook of Transportation Modeling. D. A. Hensher and K. J. Button. Oxford, UK, Pergamon**:** 211-228.

Krishnamurthi, L., S. P. Raj, et al. (1995). "Unique Inter-Brand Effects of Price on Brand Choice." Journal of Business Research **34**(1): 47-56.

Leeflang, P. S. H. and D. R. Wittink (2001). "Explaining Competitive Reaction Effects." International Journal of Research in Marketing **18**: 119-137.

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behavior. Frontiers in Econometrics. P. Zarembka. New York, Academic Press**:** 105-142.

McFadden, D. (1975). On independence, structure, and simultaneity in transportation demand analysis. Working Paper 7511, Urban Travel Demand Forecasting Project, Institute of Transportation Studies, University of California, Berkeley, CA.

McFadden, D. (1978). Modeling the choice of residential location. Spatial Interaction Theory and Planning Models. A. Karlqvist, L. Lundqvist, F. Snickars and J. Weibull. Amsterdam, Elsevier Science Ltd 75-96.

Narayanan, S., R. Desiraju, et al. (2004). "Return on Investment Implications for Pharmaceutical Promotional Expenditures: the role of marketing-mix interactions." J. Marketing **68**: 90-105.

Nerlove, M. and K. J. Arrow (1962). "Optimal Advertising Policy Under Dynamic Conditions." Economica **29**: 129-142.

Nijs, V. R., M. G. Dekimpe, et al. (2001). "The category-demand effects of price promotions." Marketing Science **20**(1): 1-22.

Steenburgh, T. J. (2007). "Measuring Consumer and Competitive Impact with Elasticity Decompositions." Journal of marketing Research **44**(4): 636-646.

Steenburgh, T. J. (2008). "The Invariant Proportion of Substitution Property (IPS) of Discrete-Choice Models." Marketing Science **27**(2): 300-307.

Steenkamp, J.-B. E. M., V. R. Nijs, et al. (2005). "Competitive Reactions to Advertising and Promotion Attacks." Marketing Science **24**(1): 35-54.

Van Heerde, H. J., S. Gupta, et al. (2003). "Is 75% of the Sales Promotion Bump Due to Brand Switching? No, Only 33% Is." Journal of Marketing Research **40**(4): 481-491.

Wansink, B. (1994). "Advertising's Impact on Category Substitution." Journal of Marketing Research, 31 (Nov): 505-515.

Williams, H. (1997). "On the formation of travel demand models and the economic evaluation measures of user benefit." Environment Plann. A **9**(3): 285-344.