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# **The Impact of Nutrient Demand and Marketing Instruments on Intra-Category Substitution**

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## **Abstract**

We examine how nutrient preference and marketing actions affect the demand of various alternatives in the category. We extend the cross attributes flexible substitution logit (CAFSL) model to model the independent and interactions effects between nutritional attributes and marketing instruments. We use simulation experiments to show that our extended CASFL model performs better than the MXL model in accurately estimating the substitution patterns.

## **Introduction**

Foods with health-related nutritional attributes, such as low-calorie and low-sugar alternatives, have been growing rapidly in demand (Sandrou and Arvanitoyannis 2000). As consumers become more health-conscious (Prasad, Strijnev, and Zhang 2008; Leeflang and van Raaij 1995), their demands for more “healthy” nutritional attributes drive them to substitute among food alternatives in a category. At the same time, consumers’ choices between healthy and unhealthy alternatives are also subject to marketing actions such as pricing and advertising (Chandon and Wansink 2012). Thus, consumers’ substitution behaviors are moderated by their sensitivity to the marketing mix instruments. In this essay, we intend to investigate how health-related nutritional attributes and marketing instruments interact to influence consumers' intra-category substitution patterns.

Nutritional attributes play an important role in consumers’ food choices. Because nutritional attributes can only be purchased as food-components, consumers switch to food products that are formulated in different ways in order to modulate nutritional outcomes. For example, sales of low-calorie foods and beverages have been growing faster than high-calorie alternatives in U.S. supermarkets during the past few years (Hudson Institute report 2015). Globally the low-calorie food market value is expected to grow at a 5.9% compounding annual growth rate (CAGR) between 2013 and 2019, from 7,400 million dollars to 10,400 million dollars (Persistence Market Research 2014).

Consumers’ switching behavior can be induced by opportunities created by the introduction of new products, factors internal to the consumer, such as health concerns, or external reasons, such as promotions or stockouts (Hamilton et al. 2014). Consumers’ desire for nutritional attributes serves as an important internal reason for intra-category substitution among

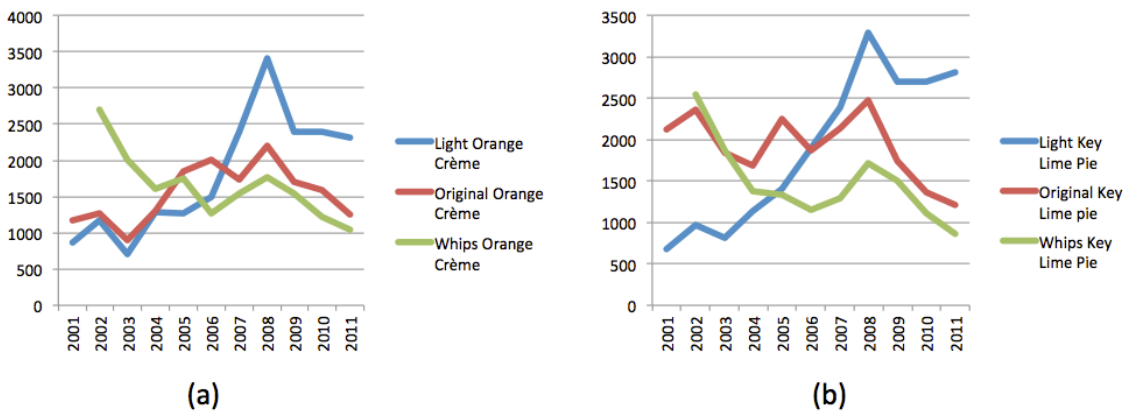
alternatives with varying nutrition content levels. Empirical studies often focus on consumers' preference and demand for low-fat or low-calorie products (Sandrou and Arvanitoyannis 2000; Czyzewska and Graham 2008), consumers' perception and response to low-fat label claims (Wansink and Chandon 2006), however, little research has examined the substitution patterns among healthier and unhealthier alternatives.

In this study, we investigate how products with varying levels of nutritional attributes draw demand from other alternatives in the same category. For example, within the yogurt categories, there are a number of low-fat and fat-free options. The introduction of a low-fat option may not only draw demand from existing options (e.g., regular and fat-free options), but also changes the relative preference among the existing options. The product substitution patterns among alternatives are affected by consumer's preference for nutritional attributes.

Figure 1 shows an example of the nutritional-profile-induced substitution in yogurt alternatives sales - units of Yoplait yogurt products bought by the IRI panel (IRI marketing data set, see data details in Bronnenberg, Kruger, and Mela 2008). In Figure 4, we compared the sales of Yoplait "light" yogurt products with Yoplait "original" and "whips" products of the same flavor (orange crème or key lime pie flavor respectively) and same package size (6-ounce). Yoplait's light yogurt is fat free (0%) whereas the other two alternatives' fat content are about 3% or 4% daily value percentage. The light alternative also contains lower calorie and less sugar than the other two alternatives. The original and whips alternatives have similar levels of fat, sugar, and calorie. The three alternatives are the main options available for the 6-ounce package Yoplait yogurt. Figure 1 shows that, in both orange crème flavor and key lime pie flavor, the sales of the light alternative has an increasing trend, whereas the other two alternatives' sales gradually decrease and become less than the light yogurt. The sales of the three alternatives in

the choice set trade off against each other, and the trading off pattern holds across the two different flavors. Thus, the substitution pattern among the alternatives is affected by consumers' preference of nutritional attributes.

**Figure 1 Yoplait yogurt products sales in 2001-2012**



Note: Orange Crème in (a) and Key Lime Pie flavor in (b)

From a manager's perspective, a better understanding of how nutritional attributes drive substitution patterns can help make important decisions regarding new product formulation, how products with different nutrient profiles are priced, and how promotion can target nutritional objectives. Managers can use the knowledge not only to make informed decision about product portfolio management, but also to identify new product and reformulation opportunities and subsequent impacts on existing products.

Whether to introduce a new product with health-related attributes is also a crucial managerial decision. While new products are typically brought out in order to achieve some switching goal, Nijs et al. (2001) shows that a successful new-product introduction can actually have a permanent category expansion effect. New-product introductions are very expensive investments, so it is essential to accurately measure the different effects of specific nutritional

attributes on sales. Accurately estimating the impact of the entry of products with improved nutritional attribute is the main objective of this study and has potential application areas include product portfolio management and new product targeting.

Preferences for a product are shaped not only by its nutritional attributes, but by how they interact with elements of the marketing mix (Singh, Hansen, and Gupta 2005). Marketing instruments have different effects on consumers' choices, leading to either expanding category demand or stealing market share from competing alternatives (Liu, Steenburgh, and Gupta 2015). For example, price promotion' impact on the demand for low-calorie products may be fundamentally different from the impact of advertising. While promotion may attract sales through switching behavior (Kumar and Leone, 1988; Walters, 1991), health-related advertising may benefit the whole low-calorie products shelf (Liu, Steenburgh, and Gupta 2015). Therefore, it is important for managers to understand the interaction effects of nutritional attribute preferences and consumers' sensitivity to marketing actions. These knowledge can help managers make informed investment decisions of product line expansion and choose the right marketing mix in their marketing plan.

Therefore, in this essay we aim to provide accurate estimates of how marketing actions affect the demand of healthy and unhealthy alternatives in the category, and to identify results that inform a wide range of marketing choices. To achieve the goals discussed above, we plan to analyze the effects and conduct empirical test with natural experiment and structural model.

## **Method**

In this section, we describe our plan of using structural model to identify the nutritional-profile-induced substitution.

In the structural approach, we proposed a structural model to accurately analyze of effects of nutritional attributes and marketing actions on consumers' substitution patterns.

The model should be able to account for cross-alternative spillover effects of nutritional attributes and marketing instruments. However, classical Random Utility Models (RUM) restrictively assume that a consumer's preference between two alternative does not depend on other option's attribute in the choice set, hence they do not allow the effects of marketing instruments to spill over to other alternatives (see discussion in Liu, Steenburgh, and Gupta 2015). Thus, in our example, the assumption would imply that introducing a low-fat option to the choice set would not affect the relative preference between the high-fat option and other options in the category. This restriction would be lead to counterintuitive estimates of how much shares the low-fat option draw from each of the other options.

In addition, RUM models possess the Invariant Proportion of Substitution (IPS) property (Steenburgh 2008). The IPS property assumes when an attribute changes for one good in the choice set, the proportion of demand drawn from other competing goods is the same, regardless of which attribute is improved (Steenburgh 2008). Formally, IPS means that the substitution ratio is constant no matter which attribute  $x_{ja}$  is improved.

$$-\frac{\frac{\partial P_k}{\partial x_{ja}}}{\frac{\partial P_j}{\partial x_{ja}}} = \Psi_{k/j} \quad \forall a$$

where  $\Psi_{k/j}$  is a constant,  $P_j$  is the probability of alternative  $j$  being chosen,  $j \neq k$ . Since we intend to differentiate the effects of various nutritional attributes and marketing instruments, the model should be able to show different proportions of demand drawn from competing options when alternative attributes are improved or various marketing actions is used. For example, it is reasonable to expect a larger proportion of demand gains when a low-salt chips product is



introduced than the demand gain when a regular-salted chips product is introduced. Another example is that different proportion of demand could be drawn when an advertisement with a general health focus is launched compared to the demand drawn when an advertisement emphasizing the low-sugar characteristic of the product is launched. RUM models could not detect these differences in the proportions of demand draws, due to the fact that they suffer from the IPS property (Steenburgh 2008).

The IPS property is different from the Independence of Irrelevant Alternatives property (IIA), which implies that the relative preference between two alternatives are the same and do not depend on the utility obtained from other alternatives. The IPS property cannot be relaxed in the usual way in which IIA is avoided, that is, with the nested logit (NL), generalized nested logit (GNL), or even random coefficient logit (RCL). RCL models can address IPS in aggregate level, but not in individual level. In RCL models, aggregate substitution ratios are not constrained by IPS property since adding heterogeneity provides flexibility in substitution patterns in aggregate. However, Liu, Steenburgh, and Gupta (2015) conducted a simulation study to show that the flexibility provided by allowing consumer heterogeneity is not wide enough to recover the substitution patterns in the simulated data, thus the random coefficient models are still not able to sufficiently relax IPS property. In individual level, the substitution ratios of RCL models do not depend on which attributed is improved, therefore IPS holds in RCL models.

We base our model on the cross attributes flexible substitution logit (CAFSL) model developed by Liu et al. (2015). The CASFL model has several advantages over classical RUM models, and is able to address our research problem in an appropriate way. First, it is the only model that addresses the IPS property. The CASFL model relaxes the IPS property by specifying an indirect utility function that includes the attributes of competing alternatives. Relaxing IPS

allows for a non-proportionate draw across attributes, and elements of the marketing mix. This feature of CASFL is very important for this study because we are particularly interested in exploring the choice set change situation – when a new product with improved health-related nutritional attributes enters into the choice set. Because nutritional attributes stay relatively fixed for a product, improvement of attributes usually occurs in new product introduction. We expect to identify varying proportions of demand drawn from the existing competing goods when different nutritional attribute is improved in the new product.

Second, the model specification also allows attributes and marketing mix effects to spill over to other alternatives. The specification of the indirect utility function includes the attributes of competing alternatives, thereby captures the possible spill over effects on the relative preference between the target product and existing product, and the relative preference between the existing products. This advantage enables the current study to examine the impact of the introduction of new product with improved nutritional attribute on the existing alternatives in the category.

Third, it's possible to produce negative cross-price elasticities to detect price complementarity, or negative spillover effects. Classical RUM models impose restrictive rules on substitution where they force all the alternatives to be strict substitutes and thus force the cross-price elasticities to be positive. In contrast, CASFL allows for non-RUM behavior so that more realistic choice behavior can be modeled.

CASFL model has many good features that suit well with our research goals, however, it mainly focuses on the spill over effects of marketing instruments. In this study, we are interested in estimating the spill over effects of nutritional attributes in addition to the marketing instruments. Therefore, we extend the model to account for the effects of nutritional attributes,

and interactions effects between these nutritional attributes and marketing instruments. We add nutritional attributes into the model and let the indirect utility function depend on the attributes, including both nutritional attributes and marketing promotions, of competing alternatives.

Following Liu, Steenburgh, and Gupta (2015), we group the choice sets into  $N$  non-overlapping nests  $B_1, B_2, \dots, B_N$ . We extend the CASFL and specify the indirect utility function for  $j$ th alternative in nest  $n$  as,

$$v_j = \alpha_i P_{ijt} + \beta(x_j + z_j) + \gamma(\sum_{l \in B_n} (x_l + z_l)) + \omega \xi_1 p_j + (1 - \omega) \xi_2 (p_j - p_n) \quad (1)$$

where  $x_j$  is non-price marketing promotion (e.g., display, feature, and advertising) and  $z_j$  is nutritional attribute (e.g., calorie, sugar, sodium) for alternative  $j, j \in B_n$ .  $\beta(x_j + z_j)$  represents the direct effect of  $x_j$  on indirect utility. To capture the possible spillover effects to other alternatives within the nest, the model adds an additional term  $\gamma(\sum_{l \in B_n} (x_l + z_l))$ . This term is the summation of attributes effects for other alternatives (denoted by subscript  $l$ ) due to the changes in  $x_j$  and  $z_j$ . An increase in  $x_j$  and  $z_j$  will have the following impacts: (i) The relative preference between alternative  $j$  and competing alternatives in the nest increases by  $\beta$ ; (ii) The relative preference between alternative  $j$  and alternatives outside the nest increases by  $\beta + \gamma$ ; (iii) The relative preference between each alternative in the nest, other than  $j$ , and alternatives outside the nest increases by  $\gamma$  (Liu, Steenburgh, and Gupta 2015). As explained in Liu, Steenburgh, and Gupta (2015), adding the term  $\gamma(\sum_{l \in B_n} (x_l + z_l))$  in the model specification provides a general framework for empirical work. If  $\gamma=0$ , it indicates that there is no spillover effect; if  $\gamma \neq 0$ , it indicates that the effect of nutritional attributes and marketing instruments on decision makers' utility spill over to other options in the nest. In the empirical test, we follow Liu, Steenburgh, and Gupta (2015) and group the four options in two nests: one nest contains the non-fat, low-fat, and regular options, and the other nest contains the no-purchase option.

In the CAFSL model specification, to capture the possible price spillover effects, Liu, Steenburgh, and Gupta (2015) followed Rajendran and Tellis (1994) to use mean price  $p_n$  as the contextual reference price.  $\omega\xi_1 p_j + (1 - \omega)\xi_2(p_j - p_n)$  implies that the total price effect is a weighted average of the alternative  $j$ 's own price effect  $\xi_1 p_j$  and the contextual reference price effect  $\xi_2(p_j - p_n)$ . Replacing the mean price  $p_n$  with  $p_n = \frac{\sum_{l \in B_n} p_l}{J_n}$ , the indirect utility function can be rewritten as,

$$v_j = \alpha_i P_{ijt} + \beta(x_j + z_j) + \gamma(\sum_{l \in B_n} (x_l + z_l)) + (\omega\xi_1 + (1 - \omega)\xi_2)p_j + \frac{(1-\omega)\xi_2}{J_n} (\sum_{l \in B_n} p_l) \quad (2)$$

This function can be re-parameterized by defining  $\beta_p = (\omega\xi_1 + (1 - \omega)\xi_2)$  and  $\gamma_p = \frac{(1-\omega)\xi_2}{J_n}$ .

Therefore, the function now becomes,

$$v_j = \alpha_i P_{ijt} + \beta(x_j + z_j) + \gamma(\sum_{l \in B_n} (x_l + z_l)) + \beta_p p_j + \gamma_p (\sum_{l \in B_n} p_l) \quad (3)$$

Then the price spillover effect is specified in the same way as the attribute spillover effect is. If  $\gamma_p$  is zero, it indicates that the price of alternative  $j$  has no price spillover effect, whereas a non-zero  $\gamma_p$  indicates the existence of price spillover effect.

Redefining  $x_j$  to include  $p_j$ , the utility function can be written as,

$$U_j = \alpha_j + \beta(x_j + z_j) + \gamma(\sum_{l \in B_n} (x_l + z_l)) + \varepsilon_j \quad (4)$$

Follow Liu, Steenburgh, and Gupta (2015), we assuming the error term in Equation (4) to have the cumulative distribution function (cdf),

$$\exp\left(-\sum_{n=1}^N (\sum_{l \in B_n} e^{-\varepsilon_l / \delta_n})^{\delta_n}\right) \quad (5)$$

Thus, the choice probability is,

$$P_j = \frac{e^{v_j / \delta_n} (\sum_{l \in B_n} e^{v_l / \delta_n})^{\delta_n - 1}}{\sum_m (\sum_{l \in B_m} e^{-\varepsilon_l / \delta_m})^{\delta_m}} \quad (6)$$

When alternative  $j$  improves its attribute  $x_{ja}$  (Note:  $x_{ja}$  represents a attribute in  $x_j$  or  $z_j$  – including price or non-price promotions, or nutritional attribute), the own- elasticity (see proof in Liu, Steenburgh, and Gupta (2015)) is given by,

$$\varepsilon_{jj} = \frac{\partial P_j}{\partial x_{ja}} \cdot \frac{x_{ja}}{P_j} = \frac{x_{ja}}{\delta_n} \left( (1 + (\delta_n - 1)P_{j|B_n} - \delta_n P_j) \beta_a + \delta_n (1 - P_n) \gamma_a \right) \quad (7)$$

the cross- elasticity among two alternatives  $j$  and  $k$  ( $j \neq k$ , and  $j, k \in B_n$ ) in the same nest  $n$  is given by,

$$\varepsilon_{jk} = \frac{\partial P_k}{\partial x_{ja}} \cdot \frac{x_{ja}}{P_k} = \frac{x_{ja}}{\delta_n} \left( ((\delta_n - 1)P_{j|B_n} - \delta_n P_j) \beta_a + \delta_n (1 - P_n) \gamma_a \right) \quad (8)$$

the cross- elasticity among two alternatives  $j$  and  $k$  ( $j \neq k$ , and  $j \in B_n, k \in B_m$ ) in different nest is given by,

$$\varepsilon_{jk} = \frac{\partial P_k}{\partial x_{ja}} \cdot \frac{x_{ja}}{P_k} = x_{ja} (P_j \beta_a + P_n \gamma_a) \quad (9)$$

the substitution ratio that represents the proportion of demand drawn for  $j$  from  $k$  is given by,

$$-\frac{\frac{\partial P_k}{\partial x_{ja}}}{\frac{\partial P_j}{\partial x_{ja}}} = \begin{cases} \frac{-P_k \left( ((\delta_n - 1)P_{j|B_n} - \delta_n P_j) \beta_a + \delta_n (1 - P_n) \gamma_a \right)}{P_j \left( (1 + (\delta_n - 1)P_{j|B_n} - \delta_n P_j) \beta_a + \delta_n (1 - P_n) \gamma_a \right)} & (j \neq k, \text{ and } j, k \in B_n) \\ \frac{-P_k (P_j \beta_a + P_n \gamma_a)}{P_j \left( (1 + (\delta_n - 1)P_{j|B_n} - \delta_n P_j) \beta_a + \delta_n (1 - P_n) \gamma_a \right)} & (j \neq k, \text{ and } j \in B_n, k \in B_m) \end{cases} \quad (10)$$

Equation (10) indicates that the substitution ratio depends on attributes (marketing instruments and nutritional attributes) specific parameters  $\beta_a$  and  $\gamma_a$ .

At the individual level, the utility of consumer  $i$  for purchase occasion  $t$  is,

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

and the no-purchase utility is given by,

$$U_{i0t} = \varepsilon_{i0t}$$

Follow Liu, Steenburgh, and Gupta (2015), we specify a random coefficient structure by letting  $\theta_i = \{\alpha_{i1}, \dots, \alpha_{iL}, \beta_i, \gamma_i\}$  and assuming  $\theta_i \sim (\theta, \Sigma)$ .

The coefficient estimates are obtained by simulated maximum likelihood (SML).

The important extension of the current study to the CAFSL model proposed by Liu et al. (2015) is the application of CASFL to non-time-varying attributes. Marketing instruments variables vary over time, providing a good source for identification of the spill over effects. In contrast, nutritional attributes are fixed over time, thus the lack of variation in nutritional attributes may lead to weak identification problem. To assess the identification ability of the model, we conduct a simulation experiment to test whether the proposed model is able to identify the nutritional attributes effects even when it is constant. The simulation experiment also tests if the model can provide accurate estimates of the varying demand drawn from competing options due to various nutritional attributes and marketing instruments – to see if the model could recover the substitution patterns in the simulated data. We also use the simulation to compare CASFL model with alternative models (e.g., Mixed Logit, RC GNL).

In the simulation experiment, we use the method of Monte Carlo Simulation. We start with generating two random marketing variables and two constant nutritional attributes variables. Then we specify the true values (mean and standard deviation) for the parameters. Using the independent variables and specified parameters in the proposed model, we generate the dependent variables. The generated data contains a total of 10000 observations, with 1000 households and 10 purchase occasions for each household and  $N=3$  choices. Lastly, we estimate the proposed model and alternative models by using the generated sample data.

For empirical test of the proposed model, we plan to use IRI market data. The following section provides detailed introduction of the data and our plan of sampling.

## Data

The empirical application use IRI (Bronnenberg, Kruger, and Mela 2008) marketing household level panel data together with matched advertising data from Competitive Media Reporting (CMR). The IRI data provides information on household's food choices, including how much they purchase, prices, and other marketing variables such as feature, display, and any other promotional activity. Because the data set is comprehensive in terms of its coverage of stock-keeping units (SKUs), we also are able to determine when new products were introduced, and how well these new products performed.

We focus on the category of yogurt. Yogurt is ideal because the nutritional attributes of yogurt products vary widely in terms of their fat, protein, sugar, and total calorie content. We consider four yogurt product sub-category options, i.e., light, regular, whips, and thick-and-creamy. We focus on the dominant package size of 6-ounce cup. We select 4 products that are most popular in the same flavor segment (e.g., strawberry, blueberry) and they are described with respect to their fat and calorie content levels (see Table1). In addition, marketing instruments variables - display and promotion are included.

Categories	Product	Style	Fat Content		Calorie Content
Yogurt	Alternative 1	Light	Fat Free	0	90 cal (light)
	Alternative 2	Whips	Low Fat	2.5g(4%)	140 cal
	Alternative 3	Original	Low Fat	2g (3%)	150 cal
	Alternative 4	Thick And Creamy	Low Fat	2.5g(4%)	180 cal

We consider households that purchased at least once in each of the four sub-category yogurt alternatives in a five-year period (2007-20011). This left 190 households and consists of a total of 3,848 purchase occasions.

## Results

Table 2 and Table 3 show the result of the Monte Carlo Simulation. We estimated CASFL and Mixed Logit model to compare their abilities to recover the true value specified in the data generating process. We conducted the simulation with both 4 alternatives and 10 alternatives (see Table 3). In both 4- and 10-product simulations, our extended CASFL provides parameter estimates that are closer to the true value than Mixed Logit does. CASFL also provides good estimates for the standard deviation for the random coefficients.

**Table 2: Simulation Study - Parameter Value and Estimates (4 alternatives)**

True Model		RC CASFL		Mixed Logit		
True Value	SD	Estimates	SD	Estimates	SD	
Alternative intercept						
$\alpha_1$	1	1.038		0.850		
$\alpha_2$	0.3	0.292		0.180		
$\alpha_3$	0.5	0.484		1.560		
Marketing instruments						
$\beta_1$	1	1	0.633	1.365	0.959	1.513
$\beta_2$	0.8	1.2	0.817	0.822	0.787	1.168
Nutritional attributes						
$\beta_3$	1.2	2	1.283	0.081	1.572	0.653
$\beta_4$	0.5	3	0.537	0.592	0.903	0.175
Summation of instruments						
$\gamma_1$	0.9	0.5	0.564	0.317	–	–
$\gamma_2$	1.3	0.7	1.356	1.105	–	–
Summation of nutritional attributes						
$\gamma_3$	1.5	1	1.503	-0.325	–	–
$\gamma_4$	1	1	1.049	0.648	–	–



**Table 3: Simulation Study - Parameter Value and Estimates (10 alternatives)**

True Model		RC CASFL		Mixed Logit		
True Value	SD	Estimates	SD	Estimates	SD	
Alternatives intercept						
$\alpha_1$	1	0.910		1.115		
$\alpha_2$	0.3	0.345		1.172		
$\alpha_3$	0.5	0.509		4.025		
$\alpha_4$	0.2	0.312		0.900		
$\alpha_5$	0.8	0.861		0.966		
$\alpha_6$	0.5	0.271		-1.325		
$\alpha_7$	1	0.983		-0.231		
$\alpha_8$	1.2	1.330		3.290		
$\alpha_9$	0.5	0.439		0.614		
Marketing instruments						
$\beta_1$	3	1	2.946	1.424	0.919	1.390
$\beta_2$	2	1	3.889	0.525	0.748	1.134
Nutritional attributes						
$\beta_3$	1	0.5	0.531	0.814	2.486	0.5822
$\beta_4$	1.2	0.7	0.677	0.498	1.132	0.1447
Summation of instruments						
$\gamma_1$	2	3	2.918	0.439	–	–
$\gamma_2$	3	1	4.405	1.231	–	–
Summation of nutritional attributes						
$\gamma_3$	0.5	0.8	0.840	-0.623	–	–
$\gamma_4$	0.7	1.2	1.088	-0.232	–	–

The simulation results indicate that our extended CASFL model performs better than the MXL model in accurately estimating the substitution patterns. With more products in the choice set, the proposed model still provides better estimates than MXL does. In addition, the extended CASFL also provides estimates on the spill over effects (i.e.,  $\gamma$  in Table 2 and Table 3) that MXL doesn't account for.

In the empirical application, we expect that the demands for certain nutritional attribute levels have positive spill over effect on more similar alternatives, and have negative spill over effects on more nutritional distinguished alternatives, and these effects are significantly moderated by marketing actions.

## **Conclusion**

In this study, we extend the cross attributes flexible substitution logit (CAFSL) model to model the independent and interactions effects between nutritional attributes and marketing instruments. We compare the modified CASFL model with traditional RUM model using simulation experiment. The simulations show that the extended CASFL model performance better in recovering substitution patterns than the MXL model.

We investigate consumers' substitution among product within a same category but have different nutritional profiles. We examine the effect of nutrient preference and marketing actions on consumers' substitution among various alternatives in the category using IRI household purchase data. The understanding of how nutritional attributes and marketing mix drive substitution patterns can help managers make informed investment decisions for product-line expansion and for choosing the right marketing mix in their marketing plan.

Future research should expand the idea of nutrient demand in other nutrient dimensions. As nutrients such as potassium, vitamin D, and added sugar receive growing public attention, FDA has recently modified the Nutrition Facts panel and added information of these nutrients to the panel. In addition, it will be interesting to explore how information of positive verses negative nutrients can have different impact on demand, especially when they are emphasized in an advertisement.

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