ELSEVIER
Journal of Retailing xxx (xxx, 2015) xxx–xxx
Journal of Retailing

Impact of Healthy Alternatives on Consumer Choice: A Balancing Act

Minakshi Trivedi[a,*], Karthik Sridhar[b,1], Ashish Kumar[c,2]

[a] *Jacobs Management Center, School of Management, The State University of New York at Buffalo, Buffalo, NY 14260, United States*
[b] *Allen G. Aaronson Department of Marketing and International Business, Zicklin School of Business, Baruch College – The City University of New York, One Bernard Baruch Way, New York, NY 10010, United States*
[c] *Department of Marketing, Aalto University School of Business, P.O. Box 21230, FI-00076 Aalto, Finland*

Abstract

While consumer screening of nutritional information as well as general health concerns have been on the rise, whether such concerns are reflected in purchasing behavior is not quite as certain. We postulate this disconnect between health concerns (more specifically concerns with fat, salt and sugar elements) and consumption behavior to stem from balancing behaviors exhibited by consumers. We address this issue through three core questions: (1) Are there certain segments of consumers who, given a focal health element, balance their purchases between healthy and regular versions of products across categories? (2) Is this balancing behavior consistent across different elements of health concern? And, (3) is a consumer's stated health orientation consistent with actual purchase behavior? We estimate a multi-category product choice model nested within an augmented latent class structure using scanner panel data and supplemented with survey based constructs obtained from the same consumers. We find evidence of significant balancing behavior across segments and also across different health elements. We show that our findings have significant implications for retail and manufacturer strategy as well as for public policy.

Keywords: Multi-category analysis; Consumption behavior; Augmented latent class model; Nutrition content; Health marketing

Consumer concern with health and nutrition issues has never been stronger. This concern is partly the result of information streaming from manufacturers, retailers, government agencies and health professionals, all of whom have a stake in promoting a healthy lifestyle. For example, the FDA (Food and Drug Administration) has implemented policies such as the 2006 Transfat Labeling Act and the 2008 Labeling Education and Nutritional Act (LEAN Act) as a means of regulating the information that manufacturers of consumer packaged goods must provide to consumers. Manufacturers are also reformulating their products with more nutritious ingredients (Megerian 2007) while retailers are featuring healthy products more prominently (Fulton 2010). A health survey conducted by the Food and Marketing Institute (FMI) reports that 32% of consumers now more than ever are switching to healthier product options including low sodium and low calorie alternatives (FMI 2012). Furthermore, 78% of consumers confirm reading nutrition labels while over 40% are willing to spend more on healthy products.

Whether such concern is reflected in actual consumer purchase behavior is not quite clear. Some studies find that the overall attitude towards nutrition changed after the labeling acts went into effect (Kozup, Creyer, and Burton 2003), while others show that the impact has been limited or negligible (Balasubramanian and Cole 2002; Moorman 1996). The latter finding is credible given reports of dramatic increases in obesity in the United States over the past 20 years with rates exceeding 25% in most states (Centers for Disease Control 2008).

Indeed, there may be several reasons for this inconsistency. Firstly, consumers may have different objectives regarding their purchases within a set of categories. For example, if certain product decisions are based on a specific health related element, such as sugar, one may consider categories such as cereal and ice cream in the same decision context. Consumers may 'treat' themselves to a regular product in one category while buying a healthy product in another. Thus, Moss (2013) reports that milk consumption has dropped by almost 75% over the years to avoid fat, while cheese consumption has simultaneously increased.

* Corresponding author. Tel.: +1 716 645 3213.
E-mail addresses: mtrivedi@buffalo.edu (M. Trivedi), Karthik.Sridhar@baruch.cuny.edu (K. Sridhar), ashish.kumar@aalto.fi (A. Kumar).
[1] Tel.: +1 646 312 3283.
[2] Tel.: +358 504 311 813.

http://dx.doi.org/10.1016/j.jretai.2015.05.003
0022-4359/

Secondly, a household may well be conscious of one health related element (such as salt) while being quite indifferent to another (such as sugar; see Prasad, Strijnev, and Zhang 2008). Finally, there could be inconsistencies between consumers' stated and actual purchase behaviors (Berning, Chouinard, and McCluskey 2011).

In order to address these issues, we formulate a heterogeneous multicategory model of choice in an augmented latent class framework, allowing consumer purchases to be correlated across categories. Our unique data set includes household scanner panel purchase data to which we append consumer survey data on attitudes and perceptions.

We find, briefly, that there are indeed segments of consumers that balance their purchasing over a set of categories with respect to a given health element. These segments, however, do not do so to the same extent nor do they do so consistently across all the health elements. Furthermore, we find that consumers' stated preferences and attitudes toward healthy choice may not always be reflected in their actual behavior. Such an understanding of consumption behavior with regards to the growing health trend has direct implications for the development of managerial strategy and public policy that actually helps to encourage and positively impact healthy consumption.

The rest of the paper is organized as follows. In the next section, we briefly review the relevant literature. We then describe our modeling approach followed by a description of the data used to estimate our models. Subsequently, we present the results of our analyses followed by a discussion of the managerial implications. We conclude with directions for future research.

Theoretical Framework

The concept of compensatory or balancing behavior has been well established in the marketing literature ever since the seminal work by Fishbein and Ajzen (1975). It has been offered as the underlying theory in a variety of contexts with balancing behavior posited over different elements (Gilbride and Allenby 2004; Hoyer 1984; Johnson, Meyer, and Ghose 1989; Wright 1975). For example, in the multiattribute choice context, a product's poor evaluation on one attribute can be balanced by its strong evaluation on another attribute (Johnson, Meyer, and Ghose 1989; Keeney 1993; Payne, Bettman, and Johnson 1993). In the market efficiency context, balancing behaviors originate from consumer beliefs of value derived from options within a choice set. In this context, balancing behavior is observed not over attributes within a product, but across products within a choice set, so that beliefs of low and high value derived through different options in the same choice set balance each other out (Chernev and Carpenter 2001). Finally, in the context of product choice, consumers may perceive that the negative evaluations of an attribute in an option can be offset by positive evaluations for the same attribute from another option within the same choice set (Chernev and Carpenter 2007). Once again, the balancing here is observed across attributes, but unlike the multiattribute context in our first example, these attributes originate in different products to balance the choice set.

It should be noted that in all prior applications, consumers aim to maximize evaluations of products or attributes across (or within) a set of products. Thus, 'poor' evaluations are compensated for by 'good' evaluations. We build on such prior findings and extend this research to the context of negatively perceived attributes – that is, attributes that, when present, generally contribute negatively to the valuation of a product. That is, we posit that consumers also exhibit such balancing behavior across a set of products when limiting the consumption of a negatively perceived attribute. We study this balancing behavior through consumer consumption for healthy products/alternatives across categories. Depending on the consumer's individual health orientation, then, a healthy choice in some categories may compensate for a less healthy choice in another category. We thus go beyond prior literature that studies an overall household level of health consciousness (see, for example, Prasad, Strijnev, and Zhang 2008) to study the balancing behavior that we posit across categories. Our study thus acknowledges the attraction of some negatively perceived attributes and the consumer's awareness of the need to minimize these, resulting in the balancing or compensatory behavior across the specific categories carrying this attribute. We thus propose our first research question with respect to *balancing behavior*: When choosing healthy products, do certain segments of consumers balance consumption of a common health element across a set of categories carrying that element?

Studies such as Moorman (1996) and Balasubramanian and Cole (2002) having studied the effects of the *Nutrition Labeling and Education Act* (NLEA) introduced by the FDA on consumer search for nutritional information, find that the act impacts only certain motivated consumers. These motivated segments then become more sensitive to certain nutrients after the implementation of the act. This consciousness may thus prevail only for some specific elements (Moorman et al. 2004) so that a household may well be extremely conscious of, for example, the sugar in their consumption but is indifferent to the amount of salt they consume.

Furthermore, prior research has shown that segment size, price sensitivities and demographic characteristics of consumers have an impact on the consumption of healthy products (Ma, Ailawadi, and Grewal 2013). Given this, we contend that such heterogeneity results not only in a variation of healthy consumption across households but also in the degree to which it is observed across different elements for a given household. Our second research question on *heterogeneous behavior* can thus be posed as the following: Is the balancing behavior heterogeneous for households across the different elements of health concern?

Note that our access to the stated preference data allows us to better incorporate and thus understand the nature of individual consumer heterogeneity (Horsky, Misra, and Nelson 2006). Furthermore, it also allows us to determine the specific element towards which the household is sensitive while the revealed (purchase) data allows us to evaluate the degree to which this sensitivity transfers to other elements. (Note that some prior research such as Balasubramanian and Cole 2002, also used scanner-panel data, but given their aggregate level focus, the incorporation of individual level heterogeneity and the tie in of demographics was not feasible.)

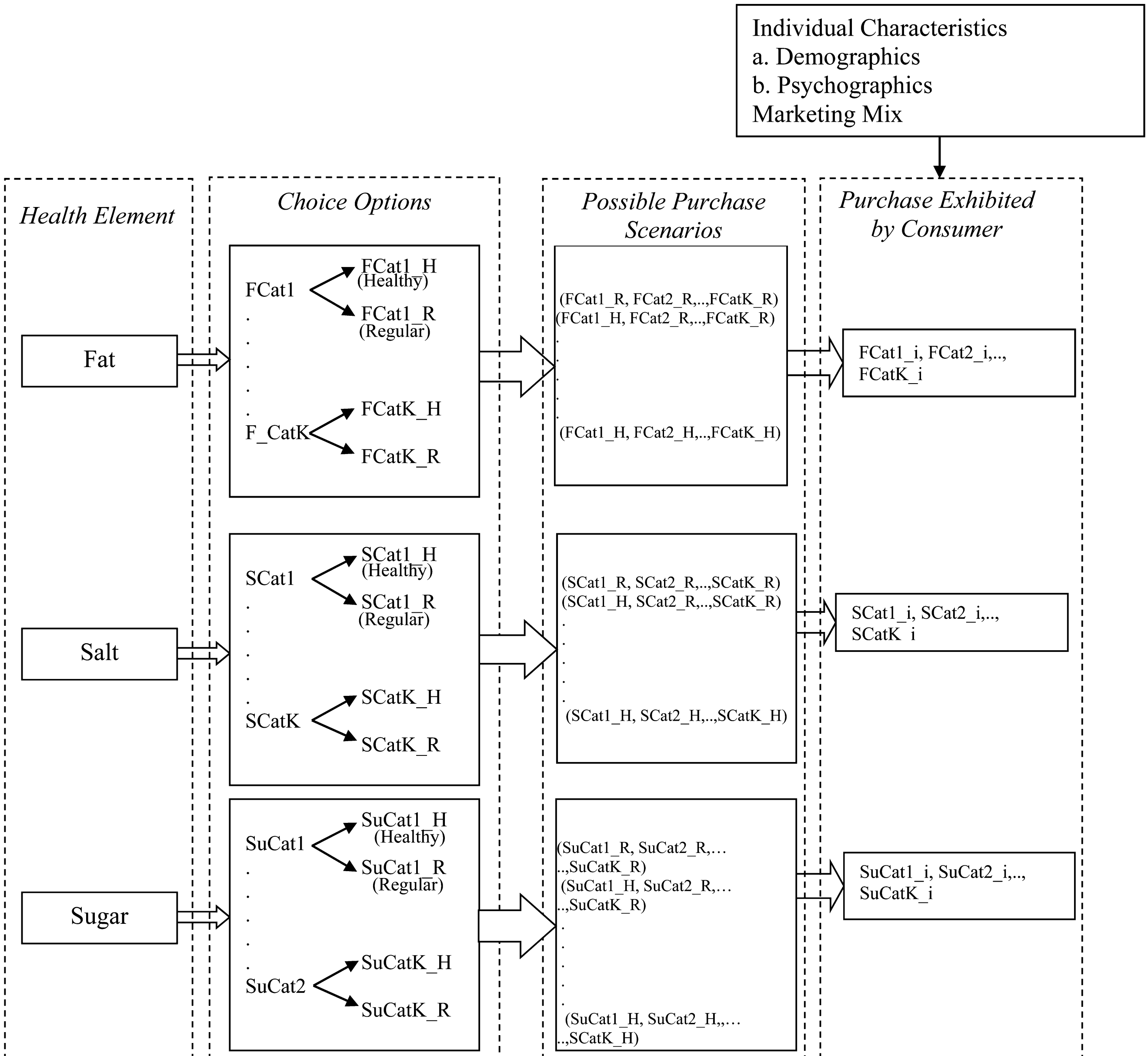

Fig. 1. Theoretical framework.

While there is a significant stream of research in the area of healthy consumption, most of these studies (e.g., Kozup, Creyer, and Burton 2003; Moorman et al. 2004; Wansink and Chandon 2006) are based on experiments using consumers' stated data rather than actual purchase data. The focus is thus on consumers' interpretation of 'healthy' (Balasubramanian and Cole 2002; Moorman 1996; Moorman 2002) and how well their consumption habits are in tune with their perceived 'healthy' persona (Oakes 2005; Raghunathan, Walker, and Hoyer 2006, etc.). Consequently, while academic research has focused on understanding consumers' stated perceptions regarding their healthy consumption, there has been little or no attempt to verify their self-concept with actual purchase patterns.

The accuracy of such measures, then, is acknowledged to be open to question. There could indeed be inconsistencies between consumer's stated purchase behavior and actual choice patterns. Research has in fact shown that consumers often overestimate the quality of their diets (Chernev and Carpenter 2011; Variyam, Shim, and Blaylock 2001) – a misperception that may well explain some of the contradiction between consumer nutritional awareness and the health epidemic. We thus pose our third research question on – *perceived and observed behavior*: Are consumers' stated measures of their health orientation consistent with their revealed choice patterns?

We present our theoretical framework in Fig. 1. Note that the K categories pertaining to one element are denoted by FCat1, FCat2 to FCatK, from which consumers can choose either the Healthy or Regular options. For instance, consumer can choose either the healthy FCat1_H option or the regular FCat1_R option within FCat1 category. This results in 2^K possible purchase scenarios ranging from purchasing only regular products from all categories {FCat1_R, FCat2_R, . . ., FCatK_R} to purchasing only healthy products across all categories {FCat1_H, FCat2_H, . . ., FCatK_H}. Similar purchase scenarios for remaining health elements are also shown in the figure. As can be seen, the consumer's choice of a specific purchase scenario for each health element will be influenced by her psychographic and demographic variables and by marketing mix variables.

Methodology

In order to address the research issues posed above, we draw upon the well-established set of multicategory choice models initially proposed by Kamakura and Russell (1989). We assume that within each product category the consumer has the option of choosing the regular version or a healthy alternative. We thus offer the following logit probability of choosing any given combination of products, m_{ht}, at time t out of all possible purchase scenarios, M_{ht} (Russell and Petersen 2000) consisting of K_{ht} categories as:

$$P_{ht}(m_{ht}|K_{ht}) = \frac{\exp[v_{ht}(m_{ht}|K_{ht})]}{\sum_{m' \in M_{ht}} \exp[v_{ht}(m'|K_{ht})]} \tag{1}$$

where household h makes purchases (of healthy or regular products) from each of the k categories at time t, such that $k_{ht} = (1, 2, \ldots, K_{ht})$. Thus, for example, if we assume 2 categories carrying both regular and healthy versions with respect to a specific element, there are four possible sets of choice options for a consumer – healthy products in both the categories, regular products in both categories, or one healthy and one regular product from either of the categories ($M_{ht} \in [\{H_1, H_2\}, \{R_1, R_2\}, \{R_1, H_2\}, \{H_1, R_2\}]$). Note that,

$$v_{ht}(m_{ht}|K_{ht}) = \sum_k (\alpha_{kh} I_k + \boldsymbol{\beta}_{\mathbf{kh}}(\mathbf{X_{kHt}} - \mathbf{X_{kRt}}) I_k) + \sum_{i=1}^{K_{ht}} \sum_{j=i+1}^{K_{ht}} \theta_{ij} I_i I_j \tag{2}$$

thus represents the deterministic component of the utility function for a set of products m_{ht}. In the above equation, k represents the category (with values ranging from 1 to K_{ht}). $\mathbf{X_{kHt}}$ and $\mathbf{X_{kRt}}$ are the vector of marketing mix variables for healthy and regular products in category k at time t. I_k is an indicator variable which when equal to 1, signifies the purchase of the healthy alternative in category k.[3] α_{kh} captures the relative intrinsic preference for the healthy product vis-à-vis regular products within a category and $\boldsymbol{\beta}_{\mathbf{kh}}$ captures the effect of marketing mix variables on choosing the healthy versus the regular product within categories. The inherent preference for regular products within each category is set to zero for identification purposes. Finally, θ_{ij} captures the interaction between healthy product purchases across categories. A positive interaction term indicates that the same versions – healthy or regular – have been chosen for both products. A negative interaction estimate signals a household consumption pattern that is reflective of balancing behavior whereby the household seeks out healthy alternatives in i (j) while seeking out regular products in j (i). Note that interpreting the estimated θ_{ij} parameters offers insights regarding the categories amongst which balancing or compensatory behavior is exhibited. *This helps us address the issues raised in research question 1.*

We then embed our heterogeneous multi-category model of choice within a modified augmented latent class framework. The Augmented Latent Class Model (ALCM), initially proposed by Varki and Chintagunta (2004), addressed the issue of the presence of individual latent class segments as well as mixtures within these segments. This model augments the existing latent class framework by allowing for a proportion of households to vary their preferences and behavior as a weighted mixture of segments, the weights being determined by a Dirichlet distribution (Kim, Fong, and Desarbo 2012). Additionally, the weights lie between 0 and 1 and the sum of the weights equal 1. We thus allow household preferences to be a mixture of segment level preferences and further extend the augmentation such that segment membership may be a function of household level demographics and psychographics or the concomitant latent class approach (Dayton and Macready 1988). The concomitant approach has been used in the more recent literature to segment consumers in various contexts such as the dynamic adoption of new financial services (Yang and Ching 2013), the use of "uso-graphics" in the absence of demographics (Wilbur, Xu, and Kempe 2013), and the use of consumer behavioral measures in order for the segmentation to be actionable (Cambra-Fierro, Melero, and Javier Sese 2014). Such a formulation allows us to extract latent segments of households as a function of choice behavior and individual level characteristics. These individual level characteristics may impact segment membership differentially across different health concerns. Thus, households may well exhibit different segment memberships across the different health elements. *Analyzing the segment membership of the same household across different health concerns addresses the issue of heterogeneous balancing behaviors raised in research question 2.*

Note that each segment represents relatively homogenous compensatory behavior, the membership to which is a function of consumer demographic and psychographic variables (Dayton and Macready 1988; Gupta and Chintagunta 1994; Kamakura and Russell 1989). In order to capture such individual level data including a 'Health Orientation' construct which we extract, we supplement our data with a survey (discussed further in the data section). By including the 'Health Orientation' construct we can determine the impact of changes in this construct on segment membership. Note that prior research has shown that segment membership calculated from latent class parameter estimates without including demographic and psychographic information do not perform as well, nor are as accurate as the concomitant latent class models which do incorporate consumer specific variables in determining segment membership (Gupta

[3] We ran the model with alternative speciation using opposite coding for indicator variables (i.e., $(1 - I_i) \times (1 - I_j)$ instead of $I_i \times I_j$ in Eq. (2)). We find that though the estimates tend to change the implications from the new formulation are not significantly different from the overall implications derived from the formulation employed in our study. We thank an anonymous reviewer for pointing this out.

Please cite this article in press as: Trivedi, Minakshi, et al, Impact of Healthy Alternatives on Consumer Choice: A Balancing Act, *Journal of Retailing* (xxx, 2015), http://dx.doi.org/10.1016/j.jretai.2015.05.003

and Chintagunta 1994). Once the household segment memberships have been derived we can compare the average health orientation scores across the segments for each of the different health elements. *Such a comparison of the extracted health orientation from the survey data with the segment membership of a household from the estimated model provides us with the data required to address research question 3*.

The aforementioned formulation enriches our study threefold. First, by using the multi-category framework for product set selection we are able to understand the compensatory behavior of consumers for regular and healthy products across multiple categories. We have, at the multi-category level, assumed a completely heterogeneous framework for inherent preferences and responses to marketing mix variables. We thus account for within-segment heterogeneity by assuming that the inherent preference, price and promotional parameters are all distributed normally with a mean and variance ($N(\bar{\beta}_{1s}, \sigma^2_{1s})$). The estimated mean captures the average response of consumers in segment s on the differential marketing mix variable; the estimated variance coefficient accounts for the variation in this response. Moreover, we capture additional heterogeneity in consumption preferences by nesting the multi-category framework within a concomitant latent class structure that also allows for mixing of segment memberships for a proportion of households. Hence, at the segment membership level we assume that the membership is influenced not only by preference parameter (ψ_{s0}) but also by the consumer demographics ($\psi_{\mathbf{s}_d}$) and psychographics ($\psi_{\mathbf{s}_p}$) captured through survey data. The latent-class structure thus adopted also accounts for cross-segment heterogeneity by allowing the responses across each segment to be different. By specifically accounting for the various forms of heterogeneity we ensure that the category level interaction effects are not confounded; the interaction terms are left to more accurately measure the association of product combinations and in our research context to identify compensatory behavior.[4]

Second, by adopting a latent class structure we ascertain that the different compensatory behaviors identified are classified into definitive groups based on commonalities observed in compensation. Finally, by adopting the augmentation process we also relax the constraint that all households belong exclusively to one specific segment. Thus, we have a proportion of households with preferences that exactly match the compensatory behaviors identified by the segments but we also allow for another set of households that exhibit compensatory behaviors identified by the mixture of all the segments. (See Appendix A for a detailed explanation of the model, its identification and estimation.)

Note that this model formulation is distinct from the Varki and Chintagunta (2004) in several ways. Unlike the estimation of segment sizes in Varki and Chintagunta (2004), we allow segment membership to be a function of household level variables in the overall framework (Dayton and Macready 1988). As alluded to earlier we also use a completely heterogeneous model assuming all the response coefficients (excluding the response coefficients for demographic variables) to be normally distributed within segments (Allenby, Arora, and Ginter 1998; Gonul and Srinivasan 1993). This extensive formulation, in addition to providing better estimates, also helps fill a gap in the literature of latent class models by incorporating heterogeneity within segments.

[4] We thank an anonymous reviewer for suggesting this clarification.

Data Description

We employ two data sets for our analysis: (a) a scanner panel data set which tracks actual purchases made by households and (b) survey data which collects psychographic and demographic information from the same households. While the former allows us to model actual purchase behavior, the latter allows us to incorporate individual level variables into the model. We begin with a discussion of the selection process used for carving our final data set.

Selection of Health Elements

The US Health and Human Services and US Department of Agriculture (2005) identify diabetes, high blood-pressure and obesity as the three most common health ailments in the country today. These are also common topics for discussion in the media (ABC News 2011; Foodeditorials.com 2012, to name just a few). We thus focus on the well-known drivers of these health related concerns – that is, sugar content, salt content and fat/cholesterol content respectively (FMI 2004; Moss 2013; Oakes 2005). The relevance of these specific elements is also evident in the nature of products available in the market. With the government putting increased pressure on food manufacturers and retailers to label fat, salt and sugar contents in their products, the latter have responded by developing products that offer reduced levels of these across a range of categories (Report Buyer 2008). We use consumption data of these three health elements for our study.

Scanner Panel Data: Category Selection, Variables and Descriptive

Clearly, the specific set of categories to choose for our multicategory framework becomes critical. In the context of preferences for salty snacks, Singh, Hansen, and Gupta (2005) used potato chips, pretzels and nachos, while in the context of complementary products, Manchanda, Ansari, and Gupta (1999) study combinations such as cake mix and frosting, and Niraj, Padmanabhan, and Seetharaman (2008) study bacon and eggs.

Our focus on consumption behavior within specific health elements also provides such a 'common context'. We thus identify a set of product categories independently within each health element that offers both healthy and regular alternatives. Thus, for the salt element, low (or no) sodium options are offered along with the regular versions in the soup, crackers, potato chips, butter, peanut butter and pasta sauce categories. Within each of the categories we identify healthy versions by searching for specific keywords as identified by USDA standards (http://www.fns.usda.gov/tn/resources/appendg.pdf) in the SKU description. These include "Low Fat", "Fat Free" and "Reduced Fat" for fat categories, "Low Salt", "Low Sodium",

Table 1
Summary statistics for categories across three focal health elements.

Focal health element	Category	Category type	Average price ($/oz)	Average discount ($/oz)	Average transaction (no./week)	Assortment	% of healthy SKU	% of sales from healthy SKU
Fat	Milk	Regular	.0230	.0030	25.246	15	75.41	78.93
		Healthy	.0210	.0020	103.908	46		
	Yogurt	Regular	.1000	.0230	37.238	137	41.95	44.91
		Healthy	.1120	.0220	5.354	99		
	Creamer	Regular	.0940	.0100	30.585	55	29.49	25.47
		Healthy	.0970	.0100	10.577	23		
	Cheese	Regular	.3220	.0700	43.846	146	11.52	8.99
		Healthy	.3190	.0410	3.331	19		
Salt	Canned soup	Regular	.1090	.0220	68.877	293	19.91	15.38
		Healthy	.1050	.0210	14.200	81		
	Potato chips	Regular	.2550	.0740	47.477	181	21.66	15.98
		Healthy	.3380	.0340	6.346	45		
	Butter	Regular	1.101	.3020	20.585	13	45.83	13.41
		Healthy	1.299	.5250	3.731	11		
	Crackers	Regular	.2930	.0610	23.854	174	15.12	22.15
		Healthy	.3240	.0630	6.815	31		
Sugar	Cola	Regular	.0285	.0080	41.977	100	41.52	45.90
		Healthy	.0306	.0092	31.854	71		
	Ice-cream	Regular	.0948	.0374	54.338	384	19.33	15.23
		Healthy	.0958	.0366	9.046	92		
	Cereal	Regular	.2393	.0667	67.092	273	13.33	10.59
		Healthy	.2095	.0308	8.177	42		
	Frozen novelties	Regular	.2350	.0514	20.677	197	25.66	27.14
		Healthy	.2591	.0315	6.608	68		

"Reduced Sodium", for salt categories and "Low Sugar", "Reduced Sugar" and "Sugar Free" for sugar categories (see Balasubramanian and Cole 2002 for a similar treatment). Secondly, we include all healthy and regular SKUs within categories that have been purchased at least three times a week across the entire consumer base. We arrive at four categories for each of the three focal elements. For the fat element we use milk, yogurt, creamer and cheese categories; for salt we use canned soup, potato chips, butter and crackers categories; and for sugar, we use cola, ice-cream, cereal and frozen novelties.[5] Given the above, our final data set captures 75% or more of the total healthy purchases and 95% of the regular purchases for any given focal element.

Our scanner panel data is from a major retail chain in the North East region of the United States, and consists of over 70 stores located across three states. The panel data tracks consumer level purchases of individual products made during any visit to a store in the retail chain. We use transaction data from August 2006 to July 2008 for our analysis. The marketing mix variables operationalized include gross price and promotion for healthy and regular alternatives within each of the categories. For both the price and promotion variable, adopting the method identified by Pauwels and Srinivasan (2004), we first calculate the per unit gross price and per unit promotion amount respectively for each SKU and share weight them by their SKU market share. Table 1 presents the descriptive statistics for the aforementioned 12 categories.[6]

As can be seen, there are marginal variations in price per unit between regular and healthy versions (less than 10%) across all but 2 of the 12 categories (both potato chips and butter charge a premium for their healthy versions). Promotions however, tend to vary a little more, with half of the categories (6 of 12) showing more than a 35% difference in promotional offers between the regular and healthy versions of the products. The number of alternatives offered (assortment) also varies widely across categories, though it should be noted that only in one category (milk) is the healthy assortment actually larger than the regular assortment. This is reflected in the highest proportion of sales (79%) coming from healthy SKUs in the milk category – the lowest is in the cheese category (9%).

Consumer Survey Data: Execution and Descriptive

We randomly selected 5,000 consumers from the scanner panel data discussed above to administer a survey designed to gather individual level psychographic and demographic data. We also collect preference and attitudinal data using the EAP scale modified to include a 5 question scale for 'health

[5] Our model was robust to increases/decreases in the product category sets for each focal element. Results were also robust to the addition of unrelated categories within the health elements. Thus, changes to categories in the basket do not lead to substantive changes in results. We thank an anonymous reviewer for suggesting this form of validation.

[6] Note that additional robustness checks were also conducted to ensure that the categories and variables were stable to the results. Details are available with the authors. We are thankful to the anonymous reviewer for this suggestion.

Please cite this article in press as: Trivedi, Minakshi, et al, Impact of Healthy Alternatives on Consumer Choice: A Balancing Act, *Journal of Retailing* (xxx, 2015), http://dx.doi.org/10.1016/j.jretai.2015.05.003

Table 2
Model comparison.

	Number of segments	Number of purchase occasions	Number of parameters		Log-likelihood		BIC	
			LCM	ALCM	LCM	ALCM	LCM	ALCM
Fat	One[a]	38,675	30	30	−26,995	−26,995	54,307	54,307
	Two	38,675	65	68	−26,009	−25,900	52,705	52,518
	Three	38,675	100	104	−25,660	−25,580	52,376	52,259
	Four	38,675	135	140	−25,650	−25,571	52,726	52,621
Salt	One	29,761	30	30	−23,420	−23,420	47,149	47,149
	Two	29,761	65	68	−23,415	−23,256	47,500	47,212
	Three	29,761	100	104	−23,110	−23,011	47,250	47,093
	Four	29,761	135	140	−23,103	−23,005	47,597	47,452
Sugar	One	37,287	30	30	−26,172	−26,172	52,660	52,660
	Two	37,287	65	68	−26,251	−25,995	53,186	52,706
	Three	37,287	100	104	−25,899	−25,783	52,851	52,661
	Four	37,287	135	140	−25,890	−25,765	53,201	53,004

[a] The one segment model for both LCM and ALCM is the traditional random-effects model.

orientation' (Baumgartner and Steenkamp 2001; Sridhar, Bezawada, and Trivedi 2012). A 3rd party was employed to administer the mail survey to protect individual privacy. The survey data was then matched with the transaction data through previously assigned unique ids. Responses were collected over a 1 month period in 2006. A help line was provided during this period to answer queries pertaining to the survey. Consumers were provided with a self-addressed envelope to mail back the surveys. To incentivize completion and improve response rates, consumers submitting completed surveys were able to take part in a lucky draw for cash rewards. The entire process yielded 1002 responses (a response rate of 20%). Of these, a total of 400 households both accurately completed the surveys as well as purchased at least once in the set of categories pertaining to at least one of the health elements; these were ultimately used for estimation.

We find from the survey data that the average household (*HHsize*) consists of 2.30 members with the average years of education (*Edu*) of the consumer primarily responsible for purchase decisions in the household being 14 years. Furthermore, the average annual household income before taxes (*Inc*) is $64,000.[7] We also conduct a factor analysis (using the varimax orthogonal rotation procedure) on the modified EAP scale and isolated the factor identified as the 'Health Orientation Score' (HOS; Cronbach's $\alpha = 0.83$) consisting of the following five statements: "*Whenever I buy a new food product, I check its nutritional information*", "*In general, I prefer to eat low fat food products*", "*I pay very close attention to the food I eat*", "*I usually get upset when I eat fattening food*" and "*I exercise regularly*". Note that the remaining factors (variety seeking tendency and risk aversion) were not relevant to this study nor did they correlate with purchasing behavior. Thus, we supplement the scanner panel data with consumer level demographic and lifestyle information obtained from the survey.

Results

Comparing the proposed model to the heterogeneous LCM model (Kamakura and Russell 1989), we can see that our model offers a better fit both in terms of log-likelihood and BIC. We use the latter to determine the optimal number of segments as it explicitly takes into account effects due to over parameterization. We report fit statistics for the benchmark models and the proposed model in Table 2.

Results for the individual analysis of all three element related sets of categories are displayed in Tables 3–5. The optimal number of segments using the BIC statistic (parameter adjusted fit statistics from the ALCM model) is three for each of the health elements.[8] All 36 intercept parameters (the inherent preferences) are significant; all price and discount parameters (36 each) are significant and in the right direction. Across all three sets of categories, the segments consist of one primarily health oriented cluster (we name this the 'Health Driven' segment); a second segment that displays a more moderate approach to purchasing healthy products (the 'Balancing' segment); and a third segment that appears to be indifferent to the healthier versions of the regular products (the 'Hedonic' segment).

In allowing for a segment of households whose preferences are a weighted mix of identified segments (as discussed earlier) we assume that there is a proportion (r) of households whose preferences and behaviors align exactly with one of the S identified segments while the other ($1 - r$) households have a tendency for emulating cross segment mixing behavior (see Web Appendix A). We find that the r estimate for the fat, salt

[7] Please note the consumer expenditure 2013 news release (http://www.bls.gov/news.release/cesan.nr0.htm) reports the average number of members in a household to be 2.5 with 1.3 average earners and an average annual income of $63,784.

[8] The optimal segments for ALCM model is lesser than the optimal number of segments identified by the LCM model for salt and sugar categories. This behavior was also noted by Varki and Chintagunta (2004).

Table 3
Parameter estimates of 3-segment model for fat.

	Health Driven (Segment 1)	Balancing (Segment 2)	Hedonic (Segment 3)
Segment level			
Intercept	0.41* (0.2297)	0.11* (0.0561)	0
HHSize	0.04 (1.0837)	−0.08* (0.0405)	0
Edu	0.09** (0.043)	0.02*** (0.0015)	0
Inc	0.86* (0.5051)	0.1 (0.0813)	0
HOS	0.49* (0.2939)	0.06* (0.0344)	0
Product choice set			
Intercept			
Milk	0.49** (0.2231)	−1.34** (0.5298)	−2.12** (0.9736)
Yogurt	0.66** (0.3064)	0.19*** (0.0155)	−1.41*** (0.0748)
Creamer	−0.08*** (0.0229)	0.26*** (0.0147)	−1.15** (0.5036)
Cheese	−0.08** (0.0384)	−0.22** (0.1044)	−0.07*** (0.0125)
Gross price			
Milk	−0.2* (0.1096)	−2.28* (1.3083)	−3.18* (1.6842)
Yogurt	−0.13** (0.0537)	−1.37** (0.642)	−0.96*** (0.3612)
Creamer	−0.28*** (0.0163)	−1.32*** (0.0971)	−1.06** (0.4359)
Cheese	−1.59** (0.7485)	−1.06*** (0.0565)	−2.21* (1.2838)
Promotion			
Milk	1.35* (0.8022)	1.67* (0.9608)	1.81* (0.9472)
Yogurt	0.08** (0.035)	0.28* (0.1658)	1.41* (0.7829)
Creamer	1.08 (3.1131)	0.35** (0.166)	0.31 (0.4946)
Cheese	0.15 (0.1531)	0.21 (0.2292)	0.65*** (0.0546)
Interactions			
Milk–Yogurt	0.32* (0.187)	0.32** (0.1526)	−0.59* (0.3583)
Milk–Creamer	0.07** (0.0343)	−0.09 (0.1012)	−0.48*** (0.0646)
Milk–Cheese	0.16** (0.0774)	−0.02 (0.0278)	−0.23*** (0.0658)
Yogurt–Creamer	0 (0.0028)	−0.07** (0.035)	−0.2 (2.8097)
Yogurt–Cheese	−0.08** (0.0355)	−0.44*** (0.1415)	−0.13*** (0.0109)
Creamer–Cheese	0 (0.013)	0.05*** (0.0142)	0.05 (0.0495)
Segment sizes	0.31	0.36	0.33

Standard errors are reported in parenthesis. *Note*: We report the means and standard errors for intercept, price and promotion variables (for Tables 3–5). The corresponding heterogeneity estimates are suppressed in the table to facilitate readability. The mixture proportion $(1 - r)$ is 0.31 and non-mixture proportion (r) is 0.69.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

and sugar elements is .69, .75 and .55 respectively. Interestingly, this reflects substantial mixing of segment behavior for households in the sugar categories ($(1 - r) = .45$), while households in the fat and salt purchasing are more strongly aligned to specific segments ($r = .69$ and .75 respectively). This has interesting implications for retail strategy and for policy makers (see Implications section).

Given that segment level behavior is significantly consistent across all three focal elements, we provide a more detailed discussion of results at the segment level.[9]

For a summary overview of the comparisons across health elements discussed below, see Table 6. (Note that we do not repeatedly refer to Table 6 as we frequently make cross health element comparisons – we leave it to the reader to refer to it for a summary picture of relative effects.)

Segment 1: Health Driven

Membership in the Health Driven segment (relative to other segments) is strongly influenced by income, education and health orientation covariates across all three focal health elements (see Tables 3–5 for individual results and Table 6 for an overview), with all consistently positive and all but one covariate being significant. Household size on the other hand, does not show a consistent pattern in significance or sign. In order to better understand purchase behavior within this segment we now explore the product set choice estimates.

Note that the inherent preference estimates for all categories in this segment are positive and significant across all three focal elements. Since these are estimated with respect to regular products we can confirm that Segment 1 consumers tend to have a positive preference for the healthy versions (as opposed to their regular counterparts) across all product categories. This evidence of consistent positive preferences in this segment is not found in either of the other two segments (2 or 3) for any of the focal elements. Clearly, this segment displays the strongest health focus – we thus name it the 'Health Driven' segment.

[9] Please note that the segment level discussions make frequent references to these 3 tables. In order to avoid frequent disruption in the reading flow we do not repeatedly reference the specific table unless we are quoting individual parameter values.

Table 4
Parameter estimates of 3-segment model for salt.

	Health Driven (Segment 1)	Balancing (Segment 2)	Hedonic (Segment 3)
Segment level			
Intercept	0.24** (0.1)	0.34 (0.8628)	0
HHSize	0.21 (0.1504)	0.03* (0.0186)	0
Edu	1.3** (0.5768)	0.45 (0.7651)	0
Inc	1.75*** (0.6143)	0.35* (0.1982)	0
HOS	1.14*** (0.0586)	0.27 (0.6154)	0
Product choice set			
Intercept			
Soup	0.46*** (0.0773)	0.23** (0.1019)	−1.2* (0.6308)
Potato chips	1.48** (0.7057)	−0.38*** (0.0338)	−0.46** (0.1862)
Butter	0.53** (0.2471)	0.45* (0.2667)	−0.05** (0.0252)
Crackers	1.13* (0.6069)	−0.18* (0.0932)	−0.04*** (0.0028)
Price			
Canned Soup	−2.4* (1.3182)	−2.43** (1.1611)	−2.57* (1.5039)
Potato chips	−2.11* (1.0829)	−2.45*** (0.1688)	−2.77** (1.3042)
Butter	−0.72** (0.3465)	−1.09* (0.5825)	−1.69** (0.7082)
Crackers	−0.56*** (0.0935)	−1.23* (0.6382)	−1.79** (0.8702)
Promotion			
Soup	0.6*** (0.049)	0.76*** (0.0382)	0.86*** (0.0665)
Potato chips	0.61** (0.2984)	0.72** (0.3669)	1.29 (0.7963)
Butter	−0.01 (0.0142)	0.37** (0.1458)	1.76*** (0.1944)
Crackers	0.19 (0.1755)	1.41** (0.5505)	1.72 (2.7415)
Interactions			
Soup–Potato chips	0.58*** (0.0348)	−0.57* (0.343)	−0.69* (0.3799)
Soup–Butter	0.12 (0.4203)	0.76* (0.4203)	−0.08*** (0.0054)
Soup–Crackers	0.29* (0.1678)	0.78** (0.3611)	−0.47 (1.8093)
Potato chips–Butter	0.16* (0.0936)	−0.44** (0.2186)	−0.14*** (0.0073)
Potato chips–Crackers	0.2*** (0.0132)	0.78* (0.4007)	−0.05*** (0.0198)
Butter–Crackers	0.25* (0.1355)	−0.55** (0.2317)	−0.18 (0.1317)
Segment sizes	0.41	0.22	0.37

Standard errors are reported in parenthesis. *Note*: We report the means and standard errors for intercept, price and promotion variables (for Tables 3–5). The corresponding heterogeneity estimates are suppressed in the table to facilitate readability. The mixture proportion $(1-r)$ is 0.25 and non-mixture proportion (r) is 0.75.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

All prices parameters are significant and have the expected (negative) signs for all categories across all focal elements. It is interesting to note that in most cases (75%) the impact of the price variable is smaller in the Health Driven segment compared to the other two segments (18 of the 24 comparisons; that is, 4 price variables within the Health Driven segment for each of the 3 focal elements compared with the other 2 segments leading to a total of $4 \times 3 \times 2 = 24$ comparisons). The 12 promotional parameters (one for each product category) also all have the right sign although only a little over half of them for the health driven segment across all three health elements are significant (7 of 12 parameters). Nevertheless, the same general pattern of comparison is observed – that is, when considering significant parameter comparisons promotions seem to play less of a role in the Health Driven segment compared to the other two segments (that is, in 90% or 9 out of 10 comparisons). Given that this segment is characterized by healthy purchasing behavior, this finding is intuitively appealing in that it signals that relative to the other 2 segments, price and promotions do not dominate decision making.

An investigation of the interaction estimates (θ_{ij}) provides further insight into the joint purchasing of healthy products between pairs of constituent categories within each focal element. A positive estimate of the θ_{ij} parameter signals an increased likelihood of purchasing the same product alternative (healthy or unhealthy) from both *i* and *j* categories. A negative parameter estimate, on the other hand, implies an increased likelihood of purchasing a regular version from only one of the two (*i* or *j*) categories – indicative of the balancing behavior we are interested in. Furthermore, the LR test conducted to ascertain the joint significance of the interaction terms was found to be significant, thus rejecting the null hypothesis that the interaction term effects are due to chance. Hence, the interaction terms in our research context play a significant role in explaining consumption balancing behavior across category sets within a focal health element.[10]

Since each of our focal elements consists of 4 product categories, we have a set of 6 interaction terms in each and a total of 18 across all 3 focal elements. Of these, two thirds (12) is significant, of which only one has a negative sign indicating that

[10] Details are available upon request. We thank our anonymous reviewer for this suggestion.

Table 5
Parameter estimates of 3-segment model for sugar.

	Health Driven (Segment 1)	Balancing (Segment 2)	Hedonic (Segment 3)
Segment level			
Intercept	0.14** (0.0697)	1.14** (0.5737)	0
HHSize	0.15** (0.0603)	−0.04 (0.057)	0
Edu	−0.02 (0.2269)	0.08*** (0.011)	0
Inc	0.62** (0.2479)	0.13*** (0.0074)	0
HOS	0.05** (0.0191)	0.01** (0.0062)	0
Product choice set			
Intercept			
Cola	0.52* (0.3021)	−0.34** (0.1706)	−0.52** (0.2267)
Ice-cream	0.64* (0.3488)	0.56** (0.2777)	−0.09*** (0.0087)
Cereal	0.06** (0.0266)	−0.19* (0.1131)	−1.29*** (0.1069)
Frozen	0.58*** (0.0489)	1.2* (0.6928)	−0.35*** (0.0201)
Price			
Cola	−0.76* (0.4083)	−0.6** (0.2786)	−0.54** (0.2379)
Ice-cream	−1.05* (0.5612)	−1.73** (0.7071)	−2.13** (1.0828)
Cereal	−0.7* (0.4015)	−0.68*** (0.0349)	−0.76*** (0.0478)
Frozen	−1.23*** (0.2882)	−2.26*** (0.1725)	−0.53** (0.2108)
Promotion			
Cola	0.36* (0.1957)	0.38 (0.3039)	0.06 (0.0915)
Ice-cream	1.15** (0.4626)	1.24** (0.6228)	0.58*** (0.22)
Cereal	1.41** (0.6506)	2.05** (0.9602)	0.81 (1.1965)
Frozen	0.47 (0.3401)	0.91 (0.7704)	0.56* (0.316)
Interactions			
Cola–Ice-cream	0.19* (0.1069)	0.14** (0.0692)	−0.9*** (0.0487)
Cola–Cereal	−0.06 (0.0876)	−0.01** (0.0052)	0.93 (1.6667)
Cola–Frozen	0.08** (0.0365)	−0.1* (0.0533)	−0.73** (0.3112)
Ice-cream–Cereal	0.09 (0.0583)	−0.02 (0.0272)	0.87** (0.4333)
Ice-cream–Frozen	0.05* (0.0248)	0.15*** (0.0167)	0.76 (1.4951)
Cereal–Frozen	−0.53 (0.6529)	0.08 (0.0658)	0.34 (0.2818)
Segment sizes	0.23	0.37	0.40

Standard errors are reported in parenthesis. *Note*: We report the means and standard errors for intercept, price and promotion variables (for Tables 3–5). The corresponding heterogeneity estimates are suppressed in the table to facilitate readability. The mixture proportion $(1 - r)$ is 0.45 and non-mixture proportion (r) is 0.55.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

in the majority of cases (92%) consumers are consistent in purchasing healthy versions of both products. Given that this is the Health Driven segment, this low level of balancing behavior is intuitively appealing – we would expect to see more of it in the more moderate Balancing segment. The only negative sign is in the fat category, where the joint purchasing of yogurt and cheese exhibits balancing behavior.

Table 6
Comparison of segments across focal health elements.

Covariate	Health Driven	Balancing	Hedonic
Inherent preference	10 of 12[a]	6 of 12	0 of 11
For healthy alternative	(83%)	(50%)	0%
Income	+++[b]	++	+
Health orientation	+++	++	+
Price	+	++	++
Promotions	+	++	++

[a] Number of intercept parameters with positive signs indicative of inherent preference for healthy alternatives.
[b] Degree of impact on preference for healthy alternatives as measured by coefficient values.

Segment 2: Balancing

Across all three focal elements, both income and health orientation have a 'medium impact' in this segment compared to the strongest impact observed in the Health Driven segment. Furthermore, inherent preferences as revealed by the intercept terms, show that preferences for the healthy version of products is displayed in 2 out of the 4 product categories (as indicated by 2 negative signs and 2 positive signs) for each of the 3 focal elements. For example, analysis for the focal element salt, displays preference for healthy versions in the soup (0.23, Table 4) and butter categories (0.45, Table 4), but regular versions in the potato chips (−0.38) and crackers categories (−0.18). Similar trends are observed for other focal elements as well. Given this middle of the road approach to healthy purchasing (confirmed further below), we call this cluster the 'Balancing' segment.

Consumers are sensitive to price across all categories and focal elements, and are in most cases (75%) more price sensitive than consumers in the Health Driven segment. In the same vein, promotional discounts have a stronger impact in most cases (8 out of 9) for consumers in the Balancing segment relative to the Health Driven segment.

A study of the interaction parameter estimates reveals that consumers do still purchase healthy products across certain category combinations as with the Health Driven segment. However, in this Balancing segment, households are far more likely to indulge in balancing behavior across the constituent categories and jointly purchase a healthy and regular product combination – for example, healthy soup with regular potato chips or vice versa (−0.57, Table 4) for the focal element of salt. Overall, the joint purchasing of one healthy and one regular product is observed in 6 of the 13 (46%) significant interaction parameters indicating that in approximately half the cases consumers are purchasing healthy versions of both products (note that this percentage is 92% in the Health Driven segment). Clearly, we observe more balancing behavior in this segment relative to the last.

Segment 3: Hedonic

Since this was the segment used as our base (for identification of parameters) in the analysis, the above discussion is with respect to this segment. Negative and significant intercept terms for all 12 parameters in this segment across all focal elements indicate a preference for regular products as opposed to their healthy alternatives in all categories. We appropriately name this the Hedonic segment.

Consumers tend to be more impacted by price and discounts relative to the other two segments – though, as would be expected, this difference is more distinctive with the Health Driven segment than with the Balancing segment. The interaction estimates are predominantly negative in this segment (10 of the 11 significant parameters, 91%) indicating that joint purchasing almost always included one healthy and one regular version of products – for example, the interaction parameter for the example mentioned above of healthy soup with regular potato chips or vice versa is −0.69 (Table 4) for the salt element. Clearly, we observe the least healthy purchasing in this segment.

To summarize, then, results from the cross-category empirical analysis above yielded three distinct segments across all three of the focal health related elements prevalent in the marketplace today. We identify the Health Driven, Balancing and Hedonic segments which show distinct variations in consumer characteristics, purchasing behavior and response to marketing mix variables. Note that the health orientation of an individual plays a significant role in determining membership in the 3 segments (see Tables 3–5). Across all three focal elements, it had the strongest impact in the Health Driven segment, and the least in the Hedonic segment (see Table 6). These findings are supported by the inherent preferences reflected in the intercept parameters of the three segments. Thus, while the Health Driven segment reflects positive parameters for all categories implying a preference for the healthy alternatives, the Hedonic segment is the mirror image reflecting negative parameters and implying preference for the regular alternatives. The Balancing segment reflects two positive and two negative values for inherent preferences for the four products, splitting purchasing into healthy and regular options. Income also shows a similar pattern – the strongest impact in the Health Driven segment and the lowest in the Hedonic segment. The price and discount parameters continue this pattern, showing the lowest impact in the Health Driven segment and the highest in the Hedonic segment (see Tables 3–5).

Discussion

In order to address managerial and strategic implications of our findings, we refer back to the research questions originally proposed.

We start by reflecting on the interaction terms that speak to our first research question – that is, *do certain segments of consumers balance consumption of a common element across a set of categories carrying that specific element?* Clearly, all three segments reflect some degree of balancing behavior. The Health Driven segment with only 1 negative interaction out of 12 significant parameters shows the least balancing behavior (in Table 3). The 11 remaining significant interactions (see Tables 3–5) and preferences display a positive sign with the joint purchasing consisting of healthy alternatives for both categories. This is certainly reasonable given that this segment, with its' high degree of health orientation and relatively low impact of price and discount variables, is driven to make healthy food choices. The other two segments – Balancing and Hedonic – on the other hand, both display significant levels of balancing behavior with 7 and 10 significant interaction terms respectively, exhibiting the negative signs indicative of balancing behavior. Interestingly, the health orientation estimates are also not too dissimilar in 2 of the 3 focal elements (see Tables 3–5). The significant differences in these two segments however, is that inherent preferences in the Balancing segment still favor some healthy alternatives, while the Hedonic segment consistently seeks out the regular versions with price and discount variables still having a major impact representing more of a driving force.

Furthermore, segment sizes differ substantially across all three health elements. (Note that households are assigned to a particular segment by revising the prior membership probabilities using Bayesian techniques as proposed by Kamakura and Russell 1989.) Thus, in case of the fat element, we find that the proportion of households exhibiting this behavior is 69% (36% from the Balancing segment and 33% from the Hedonic segment). At 31%, the Health Driven segment is clearly the smallest (see Table 3). However, for the salt related analysis, the Health Driven segment is the largest single segment at 41% (see Table 4), with balancing behavior exhibited by 59% of the households (22% + 37%). For the sugar related categories we find 77% of the households exhibiting balancing behavior (37% + 40%, see Table 5) while only 23% are Health Driven. This helps us further address our first research question regarding households exhibiting balancing behavior. Interestingly, while the majority of households do indeed tend to balance their consumption of the focal element, the actual proportion that does so varies with the element of interest.

In exploring household membership in segments across the focal elements, we also address the second research question – *Is balancing behavior heterogeneous for households across the different focal elements of health concerns?* In order to study

Table 7a
Segment membership migration between fat and salt health element.

		Salt			
		Healthy	Balancing	Hedonistic	Row totals
Fat	Healthy	59 (38%) [36%]	24 (19%) [27%]	41 (33%) [28%]	124
	Balancing	36 (25%) [22%]	24 (17%) [27%]	84 (58%) [57%]	144
	Hedonistic	69 (52%) [42%]	40 (30%) [45%]	23 (17%) [16%]	132
	Column totals	164	88	148	400

Notes: Please read '59 households who belong to the healthy segment in fat element also belong to the healthy segment in salt element. 24 households who are healthy in the fat element belong to the balancing segment in the salt element', etc. Also, the row percentages are given in parenthesis while the column percentages are presented within square brackets. Thus, the 38% in the first cell is obtained from (59/124) × 100 and the column percentage of 36% is obtained by (59/164) × 100.

this, we look at the cross segment membership (that is, membership across different health elements) for households. That is, we wish to know for example, whether a consumer identified in the balancing segment of a given focal element, crosses segments in the other two focal elements. We present the segment membership results of such an analysis in Tables 7a–7c. We find that consumers who balance purchasing over one health element do not necessarily do the same over other health elements. A majority of consumers in the Balancing segment for the fat element, for example, tend to be Hedonic for the salt (57%) and sugar (61%) elements. A smaller proportion of these consumers tend to stay within the same Balancing segment for the salt (17%) and sugar (30%) related categories. A similar pattern of membership trends is observed in the Balancing segment for salt and sugar related categories as well. A significant number of consumers who are healthy in one health element tend to remain healthy in other health elements as well. Similar asymmetric trends are observed for membership across other consumption behavior

Table 7b
Segment membership migration between fat and sugar health element.

		Sugar			
		Healthy	Balancing	Hedonistic	Row totals
Fat	Healthy	39 (31%) [42%]	40 (32%) [27%]	45 (37%) [28%]	124
	Balancing	13 (9%) [14%]	43 (30%) [29%]	88 (61%) [55%]	144
	Hedonistic	40 (31%) [43%]	65 (49%) [44%]	27 (20%) [17%]	132
	Column totals	92	148	160	400

Table 7c
Segment membership migration between salt and sugar health element.

		Sugar			
		Healthy	Balancing	Hedonistic	Row totals
Salt	Healthy	71 (77%) [43%]	10 (11%) [11%]	11 (12%) [7%]	92
	Balancing	53 (36%) [32%]	23 (16%) [26%]	72 (49%) [49%]	148
	Hedonistic	40 (25%) [24%]	55 (34%) [63%]	65 (41%) [44%]	160
	Column totals	164	88	148	400

segments for different health elements combination. To summarize, consumers are indeed heterogeneous in their purchasing behavior (and thus segment membership) of healthy alternatives across the three focal elements of health. In fact, consumers in the Balancing segment of any given focal elements are more likely to be Hedonic with respect to the other elements. This leads to some interesting managerial and public policy implications which we discuss in the next section.

We now address our third research question on contradictory behavior – *Are consumers' stated measures of health orientation consistent with their revealed choice patterns?* For studying contradictions that might prevail between stated measures and actual behavior with respect to health orientation we compare data from two sources. First, the model gives us a health orientation parameter estimate, reflective of the impact of revealed health orientations for each of the identified segments across all the focal elements. We also have (through a factor analysis of data from the survey instrument) the average factor scores for health orientation for all segments across all three elements, reflective of stated health orientations. As expected, the revealed health orientations clearly show a consistent increase in HOS parameter estimates from the Hedonic, to the Balancing, to the Health Driven segments. For example, for the fat category (Table 3) the HOS parameter estimate increases from the base of 0 for the Hedonic segment, to 0.06 for the Balancing segment to 0.49 for the Health Driven segment. The revealed behavior thus aligns the Balancing segment much more closely – almost identically in fact – to the Hedonic segment. However in the stated behavior data, as reflected in their factor scores (derived from their self-stated perceptions) (see Fig. 2), while stated scores do reveal the expected pattern with the maximum value for the Health Driven segment (0.315), followed by 0.052 and −0.622 for the Balancing and Hedonic segments respectively, the Balancing segment clearly perceives itself as more similar to the Health Driven segment than the Hedonic segment. Clearly, consumers in the balancing segment especially, perceive their purchasing behavior as more healthy than is revealed by their actual purchasing behavior. For both the other health elements, the stated behavior (Fig. 2) indicates an even stronger positive perception (for the Balancing segment) of their healthy choice behavior.

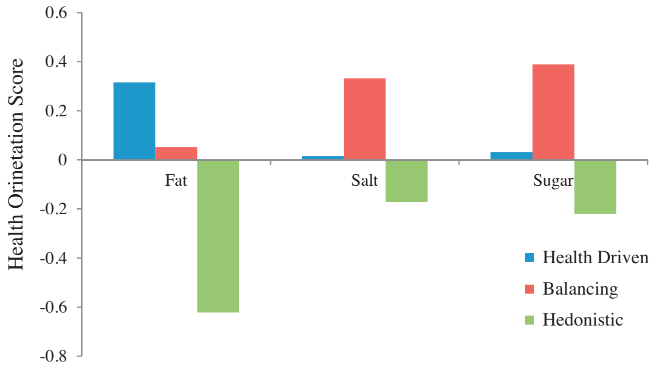

Fig. 2. Health orientation scores across three segments.

Thus, for the salt related categories, consumers in the Balancing segment actually have the highest perception of their healthy choice behavior (health orientation score of 0.3321) followed by the Health Driven segment (0.015) and lastly by the Hedonic segment (−0.172). A similar pattern is observed in the sugar related categories (0.389 for the Balancing segment; 0.031 for Health Driven segment; −0.219 for Hedonic segment).

These results indicate a marked difference between stated behavior and actual revealed behavior. With respect to research question 3, then, we find that there is indeed a disparity between stated behavior and the actual behavior exhibited.

Managerial Implications and Public Policy

We find that consumers, keeping in mind the three focal health elements, do indeed evaluate a set of categories together in making a purchase decision. Of the three segments that households fall into, two show significant balancing behavior. In spite of this outward similarity, these two segments are quite distinct in their behaviors and responses, but even more strongly divergent in their attitudes to healthy consumption. This balance is further complicated by the consumers' stated perception of healthful behavior which may in fact be overly optimistic, and furthermore, inconsistent over the different health elements. It is interesting to note the similarities in behavior of a given segment, regardless of its' composition, across the different health elements. As a result, any managerial strategy or policy implementation designed to impact consumers' healthy consumption behavior may have to be tailored to the specific segment.

Clearly, there is a demand for healthful alternatives in the market place, but this is complemented with a desire for regular 'treats' as well. The usual drivers of purchase – price and promotions – show a lower sensitivity for the Health driven segments relative to the other segments across all three health elements. Given the balancing behavior observed for multiple segments a judicious bundling of healthy alternatives may well see an improvement in overall consumption behavior. For example, given the negative interaction estimates in the fat element for both the Balancing and Hedonic segments, a bundling of retail promotions for healthy milk with healthy versions of cheese or creamer products could well improve overall healthy consumption behavior. Furthermore, the appropriate placement of such products in retail stores may also serve to promote healthier purchase patterns.

Table 8
Promotional elasticities (partial results) for fat and salt categories.

Fat categories

		Milk		Cheese	
		Healthy	Regular	Healthy	Regular
Milk	Healthy	3.11	−0.75	0.13	0.09
	Regular	−0.98	3.01	0.07	0.19
Cheese	Healthy	0.04	0.14	1.21	−0.25
	Regular	0.02	0.11	−0.27	1.82

Salt categories

		Canned soup		Crackers	
		Healthy	Regular	Healthy	Regular
Canned soup	Healthy	3.17	−0.71	0.70	0.79
	Regular	−1.12	2.94	0.23	0.53
Crackers	Healthy	0.72	0.57	2.60	−0.13
	Regular	0.89	0.38	−0.72	2.34

Note: The elasticity values should be interpreted as the impact of percentage promotional change of the row category on percentage choice probability change of the column category. For instance, a percentage promotional change in healthy milk will impact the percentage demand of regular milk by −0.74. For more explanation please see table notes in Web Appendix B.

In order to better understand this aspect, we derive promotional response elasticities for all three sets of categories relevant to each of the three elements. (Please see Web Appendix A for derivation of promotional elasticities.) Taking a closer look at the model estimates for the fat category, for example, we see that both the Hedonic as well as the Balancing segments have negative inherent preferences for healthy versions of milk and cheese (see Table 3). The derived elasticities (partial results displayed in Table 8), however, show that a promotion on the healthy version of milk not only impacts its own sales positively (elasticity = 3.11), it also depresses sales for the regular version of milk (−0.75). Note that such a promotion does more to promote healthy consumption than perhaps a sale on the healthy cheese category which has positive but relatively less impact on its own sales (1.21) and suppresses the sale of regular cheese to lesser extent as well (−0.25). Cross category bundling can also be considered so that in the salt category, for example, a promotion on healthy crackers will impact the sale of healthy soups positively (0.72). Note that the regular version of soup is also impacted positively but to a lesser degree (0.57). A promotion on healthy soup, on the other hand, while positively impacting the sale of healthy crackers (0.70) will impact the sale of regular crackers even more (0.79). This research thus offers guidance not only regarding which products to bundle for promotions, but which one of the bundle to promote in order to maximize the impact on healthy consumption. (The complete set of promotional elasticities for all elements can be found in Web Appendix B.)

These, then, represent significant public policy implications. Public health issues indicate that certain diseases such as high blood pressure and diabetes are on the rise in spite of an outcry from health industry officials and various spoke persons. This has been somewhat baffling to researchers who find that, consumers are in fact more conscientious and actually changing consumption and purchasing behaviors (Thompson 2004), none of which seems to be reflected in any national health profiles. Firstly, since most such studies have been conducted at the category level, evidence of cross category purchase behavior which we find here stays masked leading to an inaccurate profile of healthy consumption patterns. Secondly, with a majority of consumers truly believing that they are practicing healthy consumption behaviors via their balancing of certain health elements, they may in fact have to reevaluate the overall impact of their purchasing strategy. Public policy messages from agencies such as the Institute Of Medicine (IOM; an independent non-profit organization) urging that 'consumers also need to do their part by choosing healthful foods' (IOM 2010) will not be very effective if consumers feel they are already eating healthy as a result of their balancing behavior. A more specific message educating the consumer regarding the broader impact may be more effective in changing behavior. In addition, messages or strategies developed for the fat and salt health element to increase purchases of healthy products can be more focused with respect to target segments and their respective characteristics since within these health elements the households portray more focused purchase behavior and preferences and lesser mixing across segments. On the other hand, strategies being implemented in the sugar element should accommodate for significant segment mixing across households.

Conclusion and Future Research

In conclusion, this research studies consumer choice behavior in purchasing healthy alternatives to regular products. We conceptualize this behavior as a compensatory mechanism whereby consumers evaluate their choices across categories for specific health elements which they may wish to limit. We use a multicategory choice model embedded within an augmented latent class structure in a completely heterogeneous framework to understand this compensatory behavior. Our empirical results find evidence that consumers actively seek to balance their choices between healthy and regular purchases, albeit to different extents. While one extreme may seem oblivious to the benefits touted by healthy alternatives there are others that seek only healthy options in their choices. Nevertheless, we find that most consumers depending on their orientation do indeed balance their healthy choices with regular products as well. If government agencies and public policy are to have any impact in promoting healthy consumption, it is imperative to understand the nature of this compensatory mechanism and tailor strategies for specific behavioral segments. Clearly, the general one-size-fits-all approach has not worked and one can understand why.

Our approach for identifying compensatory behavior within health elements has some limitations. By adopting the Russell and Petersen (2000) framework we assume the interaction effects to be symmetrical across product categories within health elements. This assumption can be relaxed in future studies to derive more accurate insights into balancing behavior. Also, a substantial increase in the number of categories within health elements can lead to computational issues with respect to model estimation. In such cases Markov Chain Monte Carlo methodologies can be used to derive overall cross-category purchase distributions within health elements from individual full conditional category combinations (Gelmen et al. 2003).

Future research may also wish to address the issue of using a single unified framework across all health elements. Such a unified framework can also be used to address possible compensatory nature or substitutability of product categories across health elements. While this increases the number of parameters to estimate – perhaps prohibitively – if the balancing behavior across the elements is truly linked, implications from even a restricted model may offer unique insights. It is important to note that a model capturing purchasing behavior will have no means of distinguishing between a naturally low consumer of unhealthy products with a low health orientation and a health conscious consumer who is limiting his or her consumption of regular products. Future research can address the degree to which consumers lower their consumption in response to a desire to eat healthy by accommodating for quantity being purchased as well. There is also a spatial distribution issue that calls for a careful study of peer influence within regions as well as patterns of healthy purchase behavior across regions. Such spatial distribution and GIS (Geographic Information System) mapping techniques would have rich implications for marketing, but have not been researched extensively because of the difficulty in identifying precise locations of households, retail locations, etc. We leave these for future researchers to explore.

Acknowledgments

The authors gratefully acknowledge the support and contributions of the IRDF and Center for Relationship Marketing, at SUNY Buffalo, and the Center for Computational Research at the University at Buffalo for providing access to their supercomputing facilities.

Appendix A. Model Derivation and Estimation

Model Derivation

We use a standard latent choice multicategory choice model (Kamakura and Russell 1989) in order to extract the latent segments in the market. Thus, given the decision to purchase from a given category, household h makes purchases in k_{ht} categories at time t, where $k_{ht} = 1, 2, \ldots, K_{ht}$. We classify all products within each category into two subcategories – Regular and Healthy, where 'Healthy' represents the attribute free (or reduced) versions of the product. Thus the set of products available for household h at time t, given that the consumer purchased across K_{ht} categories can be defined as $\{[R_1, H_1], [R_2, H_2], \ldots, [R_{K_{ht}}, H_{K_{ht}}]\}$, where $[R_k, H_k]$ is the choice between Regular and Healthy products in category k respectively. We denote M_{ht} as all possible product combinations household h can choose to select across the K_{ht} categories at time t, conditional that the household chooses either the regular or healthy product within each category. We represent the chosen combination of products as m_{ht}. This gives us $2^{K_{ht}}$ possible product choice combinations for household h at time t. For instance, if a household buys only from one category at time t ($K_{ht}=1$) then the possible basket choices would be to pick either a regular product or a healthy product from the category. Thus, the household would derive utility from two possible product combination choices:

$$\begin{aligned} u_{Rht}(m_{ht} &= \{R\}|\{1\}) = \alpha_{1Rh} + \boldsymbol{\beta}'_{\mathbf{1h}}\mathbf{X_{1Rt}} + \varepsilon_{Rht} \\ u_{Hht}(m_{ht} &= \{H\}|\{1\}) = \alpha_{1Hh} + \boldsymbol{\beta}'_{\mathbf{1h}}\mathbf{X_{1Ht}} + \varepsilon_{Hht} \end{aligned} \tag{A1}$$

such that $\mathbf{X_{1Ht}}$ and $\mathbf{X_{1Rt}}$ represent the vector of marketing mix variables for healthy and regular products in category 1 respectively, α_{1Hh} and α_{1Rh} represent the inherent preferences for healthy and regular products respectively in category 1 and $\boldsymbol{\beta}_{\mathbf{1h}}$ is the response vector to marketing mix variables for category 1. Subtracting the utility for regular products from the healthy ones in Eq. (A1) we get:

$$\begin{aligned} u_{Rht}(m_{ht} &= \{R\}|\{1\}) = \varepsilon_{Rht} \\ u_{Hht}(m_{ht} &= \{H\}|\{1\}) = \alpha_{1h} + \boldsymbol{\beta}'_{\mathbf{1h}}(\mathbf{X_{1Ht}} - \mathrm{X_{1Rt}}) + \varepsilon_{Hht} \end{aligned} \tag{A2}$$

In the above formulation $\alpha_{1h} \equiv \alpha_{1Hh} - \alpha_{1Rh}$ is the identified preference for healthy products vis-à-vis regular products in category 1. By differencing out the marketing mix of regular products from the respective marketing mix of healthy products we are able to identify $\boldsymbol{\beta}_{\mathbf{1h}}$.

Using the standard multicategory formulation (Russell and Petersen 2000) and assuming i.i.d. extreme value distribution for the error terms, the logit probability of household h choosing set of products m_{ht} at time t out of all possible purchase scenarios (M_{ht}) consisting of K_{ht} categories is given by:

$$P_{ht}(m_{ht}|K_{ht}) = \frac{\exp[v_{ht}(m_{ht}|K_{ht})]}{\sum_{m' \in M_{ht}} \exp[v_{ht}(m'|K_{ht})]} \tag{A3}$$

where,

$$\begin{aligned} v_{ht}(m_{ht}|K_{ht}) = &\sum_{k} (\alpha_{kh} I_k + \boldsymbol{\beta}_{\mathbf{kh}}(\mathbf{X_{kHt}} - \mathbf{X_{kRt}}) I_k) \\ &+ \sum_{i=1}^{K_{ht}} \sum_{j=i+1}^{K_{ht}} \theta_{ij} I_i I_j \end{aligned} \tag{A4}$$

represents the deterministic component of the utility function for set of products in m_{ht}. In the above equation, k represents the category (with values ranging from 1 to K_{ht}) and I is an indicator variable signifying the purchase of the healthy alternative when equal to 1. α_k captures the intrinsic preference for the healthy product within a category with respect to the regular product in the same category. The inherent preference for regular products within each category is set to zero for identification purposes. $\boldsymbol{\beta}_{\mathbf{k}}$ is a vector of response to marketing mix variables on choosing the healthy versus the regular product within a category. θ_{ij} is defined as the interaction in healthy product purchases between categories i and j and hence provides insights regarding compensatory or non-compensatory purchase behavior, if any. θ_{ij} is interpreted and identified with respect to consumers opting for purchasing a regular product in either of the category combinations. Thus, the direct utilities when a household purchases across $K_{ht}=2$ categories ($M_{ht}=2^2=4$ possible product choice combinations) at time t can be written as,

$$\begin{aligned} u_{RRht}(m_{ht} &= \{R, R\}|\{2\}) = \varepsilon_{RRht} \\ u_{HRht}(m_{ht} &= \{H, R\}|\{2\}) = \alpha_{1h} + \boldsymbol{\beta}'_{\mathbf{1h}}(\mathbf{X_{1Ht}} - \mathbf{X_{1Rt}}) + \varepsilon_{HRht} \\ u_{RHht}(m_{ht} &= \{R, H\}|\{2\}) = \alpha_{2h} + \boldsymbol{\beta}'_{\mathbf{2h}}(\mathbf{X_{2Ht}} - \mathbf{X_{2Rt}}) + \varepsilon_{RHht} \\ u_{HHht}(m_{ht} &= \{H, H\}|\{2\}) = \alpha_{1h} + \alpha_{2h} + \boldsymbol{\beta}'_{\mathbf{1h}}(\mathbf{X_{1Ht}} - \mathbf{X_{1Rt}}) \\ &\quad + \boldsymbol{\beta}'_{\mathbf{2h}}(\mathbf{X_{2Ht}} - \mathbf{X_{2Rt}}) + \theta_{12} + \varepsilon_{HHht} \end{aligned} \tag{A5}$$

Assuming the existence of definitive segments within which the buyer shops for a definitive set of products for the entire household, we can then allow household preferences to be a mixture of segment level preferences. We thus embed our multi-category model of choice within the augmented latent class framework (Varki and Chintagunta 2004). Incorporating a latent class formulation, we allow s (=1, 2, . . ., S) segments such that each segment represents relatively homogenous compensatory behavior as a function of its demographic and psychographic variables (Dayton and Macready 1988; Gupta and Chintagunta 1994; Kamakura and Russell 1989). The probability that household h belongs to segment s ($Z_h(s)$) is thus given by:

$$Z_h(s) = \frac{\exp(\psi_{s_0} + \boldsymbol{\psi}_{\mathbf{s}_d}\mathbf{D_h} + \boldsymbol{\psi}_{\mathbf{s_p}}\mathbf{P_h})}{\sum_{s'=1}^{S} \exp(\psi_{s'_0} + \boldsymbol{\psi}_{\mathbf{s}'_d}\mathbf{D_h} + \boldsymbol{\psi}_{\mathbf{s'_p}}\mathbf{P_h})} \tag{A6}$$

where $\mathbf{D_h}$ is vector of household level demographic variables and $\mathbf{P_h}$ is a vector of psychographic variables. To identify parameter vector $\boldsymbol{\psi}_{\mathbf{s}} = [\,\psi_{s_0} \quad \boldsymbol{\psi}_{\mathbf{s_d}} \quad \boldsymbol{\psi}_{\mathbf{s_p}}\,]$ we normalize the utility derived by consumers for being in one of the segments as 0. The household now chooses to purchase a set of products given its membership in a segment. Hence the probability that the consumer chooses set of products m_{ht} given the categories (K_{ht}) and membership of segment s is:

$$P_{ht}(m_{ht}|K_{ht}, s) = \frac{\exp[v(m_{ht}|K_{ht}, s)]}{\sum_{m' \in M_{ht}} \exp[v(m'|K_{ht}, s)]} \tag{A7}$$

The unconditional probability that household h chooses set of products m_{ht} is hence given by:

$$P_{ht}(m_{ht}|K_{ht}) = \sum_{s=1}^{S} Z_h(s) \times P_h(m_{ht}|K_{ht}, s) \tag{A8}$$

In order to incorporate the mixing of households across segments along the lines of Varki and Chintagunta (2004) we assume that there is proportion (r) of households whose preferences and behaviors align exactly with one of the S identified segment while the other $(1-r)$ households have a tendency for emulating cross segment mixing behavior.[11] Thus, for these $(1-r)$

[11] When $r=1$ the model reduces to the traditional latent class structure.

households portraying segment mixture behavior, the conditional probability of choosing set of products m_{ht} at time t is given by:

$$P'_{ht}(m_{ht}|K_{ht}) = \sum_{s=1}^{S} g_{hs} \times P_{ht}(m_{ht}|K_{ht}, s) \tag{A9}$$

where g_{hs} is the sth component of g_h, the value drawn from a Dirichlet distribution.

Note that we model for multicategory purchase across categories while allowing segment membership to be a function of household level variables. We also use a completely heterogeneous model assuming all the response coefficients (excluding the response coefficients for demographic variables) to be normally distributed within segments (Allenby, Arora, and Ginter 1998; Gonul and Srinivasan 1993). For instance, if β_{Mhs} captures the response by consumer h to the differential price between healthy and regular milk in segment s in the fat health element, we assume that β_{Mhs} is drawn from a normal distribution $N(\bar{\beta}_{Ms}, \sigma^2_{Ms})$. While the estimated $\bar{\beta}_{Ms}$ captures the mean response that consumers within segment s would have on the differential pricing between healthy and regular milk, the estimated coefficient σ^2_{Ms} accounts for the variation in this response across all the segment s consumers. A similar approach is adopted for the response parameters that we estimate within each of the segments. Such an extensive formulation, in addition to providing better estimates, also helps bridge a gap in the literature of latent class models with continuous support points incorporating heterogeneity within segments.

Model Estimation

The model described requires estimation of the following set of parameters for a S-segment model.

For segment membership: A set of $(S-1)\times 5$ coefficient responses for segment membership denoted by $\Lambda = \{(\psi_1^1, \psi_2^1, \ldots, \psi_5^1), \ldots, (\psi_1^{S-1}, \psi_2^{S-1}, \ldots, \psi_5^{S-1})\}$, such that the set of S parameters capture the relative influence of each segment in the preference of the household denoted by $G = \{g_1, g_2, \ldots, g_S\}$ and the mixture coefficient denoted by q.
For the product set choice: A set of K heterogeneous parameters (for K categories) of healthy product preference denoted by $A = \{\alpha_{1h}, \ldots, \alpha_{Kh}\}$, K heterogeneous response coefficients each for price $B^1 = \{\beta^1_{1h}, \ldots, \beta^1_{Kh}\}$, and discounts $B^2 = \{\beta^2_{1h}, \ldots, \beta^2_{Kh}\}$ and $(K \times (K-1))/2$ non-heterogeneous interaction terms denoted by $\Theta = \{(\theta_{12}, \ldots, \theta_{1K}), (\theta_{23}, \ldots, \theta_{2K}), \ldots, (\theta_{(K-1)K})\}$ for each of the S segments.[12]

Hence, for a 3 segment model across 4 categories we would estimate 10 coefficients for segment membership, 3 parameters for relative segment influence, 1 parameter for mixture coefficient, 8×3 parameters each for preference, price and discount and 6×3 parameters for interaction yielding a total of 104 parameters. Note that the necessary condition that the number of data points be well above the number of parameters to be estimated (for identification) is satisfied. Note also that we assure identification through the positive definite Hessian derived in the estimation process (Dillon and Mulani 1989; Varki and Chintagunta 2004).

We use Simulated Maximum Likelihood Estimation (SMLE) technique (Mehta 2007; Train 2003) to estimate the model parameters. We employ MATLAB software and associated statistical toolbox functions to conduct the SML estimation. The likelihood function is given as:

$$L = \int_A \int_{B^1} \int_{B^2} \left[\prod_{h=1}^{H} \left(r \times \left[\prod_{t=1}^{T} \sum_{s=1}^{S} Z_h(s) \times P_{ht}(m_{ht}|K_{ht}, s) \right] + (1-r) \times \left\{ \int_{g_{hs}} \prod_{t=1}^{T} P'_{ht}(m_{ht}|K_{ht}) dF(g_h) \right\} \right) |A, B^1, B^2 \right] \tag{A10}$$

We use Halton draws to simulate the integral over the heterogeneous parameter space as they help keep the simulation error low with respect to number of draws compared to random draws (Train 2003). We use100 draws for each of the individual level parameters of the model. We also confirm the robustness of the new results by running the estimation with larger number of Halton draws (200 and 250 draws) and finding similar results. We also rerun the model with different starting values to ensure reliability of final estimates.

Additional References

Dillon, William R. and Narendra Mulani (1984), "A Probabilistic Latent Class Model for Assessing Inter-Judge Reliability," *Multivariate Behavioral Research*, 32 (2), 222–32.

Mehta, Nitin (2007), "Investigating Consumers' Purchase Incidence and Brand Choice Decisions Across Multiple Product Categories: A Theoretical and Empirical Analysis," *Marketing Science*, 26 (2), 196–217.

Train, Kenneth (2003), *Discrete Choice Methods with Simulation*, Berkley, CA: Cambridge University Press.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jretai.2015.05.003.

References

ABC News (2011), "Will New Food Labels Mean Better Choices?," *ABC News* (accessed October 8, 2013), [available at http://abcnews.go.com/blogs/health/2011/10/21/will-new-food-labels-mean-better-choices/].

Allenby, Greg M., Neeraj Arora and James L. Ginter (1998), "On the Heterogeneity of Demand," *Journal of Marketing Research*, 35 (3), 384–9.

[12] Note that for each heterogeneous parameter we have to estimate a mean and a standard deviation. So, if we have K heterogeneous coefficients we are actually estimating $K \times 2$ parameters.

Balasubramanian, Siva and Catherine Cole (2002), "Consumer's Search and Use of Nutritional Information," *Journal of Marketing Research,* 66 (2), 112–27.

Baumgartner, Hans and Jan-Benedict E.M. Steenkamp (2001), "Response Styles in Marketing Research: A Cross-National Investigation," *Journal of Marketing Research,* 38 (2), 143–56.

Berning, Joshua P., Hayley H. Chouinard and Jill J. McCluskey (2011), "Do Positive Nutrition Shelf Labels Affect Consumer Behavior? Findings From a Field Experiment with Scanner Data," *American Journal of Agricultural Economics,* 93 (2), 364–9.

Cambra-Fierro, Jesus, Melero Iguacel and Sese F. Javier (2014), "Managing Complaints to Improve Customer Profitability," *Journal of Retailing 91 (1),* 91 (1), 109–24.

Centers for Disease Control (2008), "Physical Activity and Good Nutrition Essential Elements to Prevent Chronic Diseases and Obesity 2008," *CDC website* (accessed October 8, 2013), [available at http://www.cdc.gov/nccdphp/publications/aag/pdf/dnpa.pdf].

Chernev, Alexander and Gregory S. Carpenter (2001), "The Role of Market Efficiency Intuitions in Consumer Choice: A Case of Compensatory Inferences," *Journal of Marketing Research,*, 349–61.

——— and ——— (2007), "Jack of All Trades or Master of One? Product Differentiation and Compensatory Reasoning in Consumer Choice," *Journal of Consumer Research,* 33 (4), 430–44.

——— and ——— (2011), "The Dieter's Paradox," *Journal of Consumer Psychology,* 21 (2), 178–83.

Dayton, Mitchell C. and George B. Macready (1988), "Concomitant-Variable Latent Class Models," *Journal of the American Statistical Society,* 83 (401), 173–9.

Fishbein, Martin and Icek Ajzen (1975), *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research,* Reading, MA: Addison-Wesley.

Food Marketing Institute (2004), *Trends in the United States: Consumer Attitudes & the Supermarket,* Washington, D.C.: Food Marketing Institute.

Food Marketing Institute (2012), "Prevention Magazine and Food Marketing Institute Reveal 20th Annual "Shopping For Health" Survey Results," *FMI* (accessed October 8, 2013), [available at http://www.fmi.org/news-room/latest-news/view/2012/07/17/prevention-magazine-and-food-marketing-institute-reveal-20th-annual-shopping-for-health-survey-results].

Foodeditorials.com (2012), "Hottest Food Trends," *Foodeditorials.com* (accessed October 9, 2013), [available at http://www.streetdirectory.com/food_editorials/meals/food/hottest_food_trends.html].

Fulton, April (2010), "Nudging Grocery Shoppers Toward Healthy Food," *NPR* (accessed October 18, 2013), [available at http://www.npr.org/templates/story/story.php?storyId=131074210].

Gelmen, Andrew, John B. Carlin, Hal S. Stern and Donald B. Rubin (2003), *Bayesian Data Analysis,* London: Chapman and Hall.

Gilbride, Timothy J. and Greg M. Allenby (2004), "A Choice Model with Conjunctive, Disjunctive, and Compensatory Screening Rules," *Marketing Science,* 23 (3), 391–406.

Gonul, Fusun and Kannan Srinivasan (1993), "Consumer Purchase Behavior in a Frequently Bought Product Category: Estimation Issues and Managerial Insights from a Hazard Function Model with Heterogeneity," *Journal of the American Statistical Association,* 88 (424), 1219–27.

Gupta, Sachin and Pradeep K. Chintagunta (1994), "On Using Demographic Variables to Determine Segment Membership in Logit Mixture Models," *Journal of Marketing Research,* 31 (February), 128–36.

Horsky, Dan, Sanjog Misra and Paul Nelson (2006), "Observed and Unobserved Preference Heterogeneity in Brand-Choice Models," *Marketing Science,* 25 (4), 322–35.

Hoyer, Wayne D. (1984), "An Examination of Consumer Decision Making for a Common Repeat Product," *Journal of Consumer Research,* 11 (December), 822–9.

Institute of Medicine (2010), *Strategies to Reduce Sodium Intake in the United States,* Washington, D.C.: The National Academies Press.

Johnson, Eric J., Robert J. Meyer and Sanjoy Ghose (1989), "When Choice Models Fail: Compensatory Models in Negatively Correlated Environments," *Journal of Marketing Research,* 26 (3), 255–70.

Kamakura, Wagner A. and Gary J. Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research,* 26 (November), 379–90.

Keeney, Ralph L. (1993), *Decisions with Multiple Objectives: Preferences and Value Trade-Offs,* New York: Cambridge University Press.

Kozup, John C., Elizabeth H. Creyer and Scot Burton (2003), "Making Healthful Food Choices: The Influence of Health Claims and Nutrition Information on Consumers' Evaluations of Packaged Food Products and Restaurant Menu Items," *Journal of Marketing,* 67, 19–34.

Kim, Sunghoon, Duncan K.H. Fong and Wayne S. Desarbo (2012), "Model-Based Segmentation Featuring Simultaneous Segment-Level Variable Selection," *Journal of Marketing Research,* 49 (5), 725–36.

Ma, Yu, Kusum Ailawadi and Dhruv Grewal (2013), "Soda Versus Cereal and Sugar Versus Fat: Drivers of Healthful Food Intake and the Impact of Diabetes Diagnosis," *Journal of Marketing,* 77 (3), 101–20.

Manchanda, Puneet, Asim Ansari and Sunil Gupta (1999), "The "Shopping Basket": A Model for Multicategory Purchase Incidence Decisions," *Marketing Science,* 18 (2), 95–114.

Megerian, Christopher (2007), "Are Diet Foods the Real Thing?," *Businessweek* (accessed October 8, 2013), [available at http://www.businessweek.com/stories/2007-08-14/are-diet-foods-the-real-thing-businessweek-business-news-stock-market-and-financial-advice].

Moorman, Christine (1996), "A Quasi Experiment to Assess the Consumer and Informational Determinants of Nutrition Information Processing Activities: The Case of the Nutrition Labeling and Education Act," *Journal of Public Policy and Marketing,* 15 (1), 28–44.

——— (2002), "Consumer Health under the Scope," *Journal of Consumer Research,* 29 (1), 152–8.

Moorman, Christine, Kristin Diehl, David Brinberg and Blair Kidwell (2004), "Subjective Knowledge, Search Locations, and Consumer Choice," *Journal of Consumer Research,* 31 (3), 673–80.

Moss, Michael (2013), *Salt, Sugar, Fat: How the Food Giants Hooked us,* New York: Random House.

Niraj, Rakesh, V. Padmanabhan and P.B. Seetharaman (2008), "A Cross-Category Model of Households' Incidence and Quantity Decisions," *Marketing Science,* 27 (2), 225–35.

Oakes, Michael E. (2005), "Bad Company: The Addition of Sugar, Fat, or Salt Reduces the Perceived Vitamin and Mineral Content of Foods," *Food Quality and Preference,* 16, 111–9.

Pauwels, Koen and Shuba Srinivasan (2004), "Who Benefits from Store Brand Entry?," *Marketing Science,* 23 (3), 364–90.

Payne, John W., James R. Bettman and Eric J. Johnson (1993), *The Adaptive Decision Maker,* New York: Cambridge University Press.

Prasad, Ashutosh, Andrei Strijnev and Qin Zhang (2008), "What can Grocery Basket Data Tell us About Health Consciousness?," *International Journal of Research in Marketing,* 25 (4), 301–9.

Raghunathan, Rajagopal, Rebecca E. Walker and Wayne D. Hoyer (2006), "The Unhealthy = Tasty Intuition and Its Effects on Taste Inferences, Enjoyment, and Choice of Food Products," *Journal of Marketing,* 70 (October), 170–84.

Report Buyer (2008), "Low-Fat & Reduced-Sugar Foods Market Assessment," *Report Buyer*.

Russell, Gary J. and Ann Petersen (2000), "Analysis of Cross Category Dependence in Market Basket Selection," *Journal of Retailing,* 76 (3), 367–92.

Singh, Vishal P., Karsten T. Hansen and Sachin Gupta (2005), "Modeling Preferences for Common Elements in Multicategory Brand Choice," *Journal of Marketing Research,* 42 (2), 195–209.

Sridhar, Karthik, Ram Bezawada and Minakshi Trivedi (2012), "Investigating the Drivers of Consumer Cross-Category Learning for New Products Using Multiple Data Sets," *Marketing Science,* 31 (4), 668–88.

Thompson, Craig J. (2004), "Marketplace Mythology and Discourses of Power," *Journal of Consumer Research,* 31 (1), 162–81.

U.S. Department of Health and Human Services and U.S. Department of Agriculture (2005), "Dietary Guidelines for Americans 2005," *research report* [available at http://www.health.gov/dietaryguidelines/dga2005/document/pdf/DGA2005.pdf].

Please cite this article in press as: Trivedi, Minakshi, et al, Impact of Healthy Alternatives on Consumer Choice: A Balancing Act, *Journal of Retailing* (xxx, 2015), http://dx.doi.org/10.1016/j.jretai.2015.05.003

Variyam, Jayachandran N., Young Shim and James Blaylock (2001), "Consumer Misperceptions of Diet Quality," *Journal of Nutrition Education,* 33 (6), 314–21.

Varki, Sajeev and Pradeep K. Chintagunta (2004), "The Augmented Latent Class Model: Incorporating Additional Heterogeneity in the Latent Class Model for Panel Data," *Journal of Marketing Research,* 41 (2), 226–33.

Wansink, Brian and Pierre Chandon (2006), "Can 'Low-Fat' Nutrition Labels Lead to Obesity?," *Journal of Marketing Research,* 43 (4), 605–17.

Wilbur, Kenneth C., Linli Xu and David Kempe (2013), "Correcting Audience Externalities in Television Advertising," *Marketing Science,* 32 (6), 892–912.

Wright, Peter (1975), "Consumer Choice Strategies: Simplifying vs. Optimizing," *Journal of Marketing Research,* 12 (February), 60–7.

Yang, Batao and Andrew T. Ching (2013), "Dynamics of Consumer Adoption of Financial Innovation: The Case of ATM Cards," *Management Science,* 60 (4), 903–22.

Please cite this article in press as: Trivedi, Minakshi, et al, Impact of Healthy Alternatives on Consumer Choice: A Balancing Act, *Journal of Retailing* (xxx, 2015), http://dx.doi.org/10.1016/j.jretai.2015.05.003