Consumer Maximization of Utilitarian and Informational Reinforcement:

Comparing Two Utility Measures to Social Class

Abstract

Based upon the Behavioral Perspective Model (BPM), previous study showed that consumers tend to maximize utility as a function of the level of utilitarian (functional) and informational (social) reinforcement offered by brands. A model of consumer brand choice was developed, which applied a Cobb-Douglas utility function to the parameters that constitute the BPM, using consumer panel data. The present paper tested a variation of the previous model, which allows for measures of consumer utility at the level of aggregate household, in addition to utility per consumed product unit (e.g., gram), and examined the relations of obtained utility with consumers' social class and age. Results indicate that the model fitted the data well, generating consistent parameters, and that utility per product unit, but not total household utility, was positive correlated to social class. These findings suggest that, in the case of supermarket food items, higher-income households obtain higher levels of utility than lower-income households by purchasing brands that offer more utilitarian and informational reinforcement per product unit rather them buying larger quantities of brands offering lower reinforcement levels.

Keywords: consumer behavior analysis; utility maximization; behavior perspective model; supermarket food items; consumer behavior; social class.

Introduction

Behavior analysis, with its emphasis on the experimental investigation of the effects of situational variables upon individual behavior, can be defined as a natural science (Baum, 2005), which should explain the individual behavior responsible for phenomena studied by social sciences, such as economics (Skinner, 1953, p. 400). Consumer behavior analysis consists of a research program that follows this direction, envisaged by Skinner, of providing interpretation and explanation to social phenomena related to consumption. In this sense, the conceptual framework of the program is built from behavior analysis and behavioral economics, whereas the behavior of interest is closely related to strategies and practices adopted in marketing.

Research in consumer behavior analysis has been predominantly inspired by the Behavioral Perspective Model (BPM), an approach based upon behavior analysis and behavioral economics particularly developed to interpret and explain consumer behavior (cf. Foxall, 1990, 1998, 2002, 2010). According to the model, consumer behavior occurs at the consumer situation, which consists of the intersection of the consumer's learning history and the current consumer behavior setting, producing environmental consequences (reinforcement and punishment). These consequences of a consumer behavior alter the probability of its recurrence in similar settings on future occasions. Therefore, elements and events in the consumer setting, such as a specific product or brand, acquire discriminative function due to their association to the consequences of buying or consuming certain products and services. In this manner, the model upholds that these consequences will influence or even determine consumer choice, regarding brands, services, products or any other consumer-related behavior. One interesting characteristic of consumer behavior is that it typically involves both reinforcing and punishing consequences, when one considers that even highly reinforced responses are also accompanied by some punishers, such as monetary costs or time investment (Foxall,1998).

The BPM, in adapting the behavior-analytic framework to the context of consumer choices, proposes that consumer behavior is mainly influenced by two types of consequences, utilitarian and informational, which can function as reinforcement or as punishment. Utilitarian consequences are directly related to the use or consumption of products and services, whose physical characteristics and practical benefits strengthen (reinforcers) or weaken (punishers) the probability of acquiring the product or service. For example, the major utilitarian reinforcement associated to owning a car is to have door-to-door transportation. Other characteristics can also have utilitarian function as additional attributes provided by the product, such as, in the car example, air-conditioner, extra engine power, and such like.

Informational consequences are mediated by other persons, resembling what Skinner (1957/1992) identified as social and verbal consequences. In the context of consumer behavior, these consequences are related to symbolic elements of the consumer context, which can be defined as status, prestige or social feedback (either positive or negative) that are associated with a particular purchase or consumptive behavior (Foxall, 1998). In the car example, programmed social reinforcement, in the form of social status, is usually higher if the car make is a famous brand, such as a Bentley or a Mercedes rather than a Renault, given similar car models. Independently of the make of the car, the consumer would get door-to-door transportation, (i.e., the basic utilitarian reinforcement), but owning a prestigious car make is likely to increase social admiration and approval. Informational consequences function as feedback to the consumer, mediated by other persons, concerning his or her performance as a consumer. Acquiring famous and well-known brands is typically associated to increased probability of producing informational reinforcement, as these brands are viewed by most people as producing high quality products, purchasing them is frequently praised and admired.

In practice, when identifying consequences as having utilitarian or informational functions, one is usually referring to what functions as reinforcement (or punishment) for the majority of people in most situations. However, this does not imply that every attribute will have the same function to every individual consumer in any situation. A given product attribute or characteristic may function as utilitarian reinforcement for one consumer and as informational reinforcement to another consumer, considering that the history of each individual will determine what events in the setting indicate utilitarian and informational reinforcers (and punishers). In practice, however, when it has been necessary to analyze informational and utilitarian reinforcement in the market, in general, previous works have considered that in any given market there are attributes and characteristics that function as utilitarian or informational reinforcement for most consumers in a given consumer segment, which usually add to the product price.

Considering that consumer's choices are influenced by reinforcement and punishment, increasing with the amount of reinforcement and decreasing with the amount of punishment (e.g., amount of money payment), it can be derived from the BPM the prediction that consumer choices should tend to maximize utilitarian and informational reinforcement given a certain amount of money to spend, that is, given a budget.

This prediction might shed light on the explanation of several phenomena related to consumer behavior, for which there is no integrative theoretical framework. Despite the fact that the literature on consumer behavior is very diverse in theoretical and methodological orientations, two general tendencies have been predominant in the field. The first of them is heavily inspired by social-cognitive theories, mostly originated in psychology, which attempts to identify the cognitive processes that cause consumer choices. This line of enquiry has mirrored its counterpart in psychology by developing dozens of dualistic micro-theories that are very specific and limited in scope. Typically, this kind of research explains consumer behavior by inferring the occurrence of constructs that impact on what people do. The constructs adopted are numerous and diverse, and usually inferred from consumers' verbal reports. To give some examples, in contemporary issues of much cited journals (e.g., *Journal of Consumer Research*; *Journal of Consumer Psychology*), the following constructs have been used: extended self, involvement, greed perception, self-expression, brand personality, brand attachment, executive attention, mindsets, among many others.

The other predominant approach that has produced relevant research about consumer behavior, although somewhat indirectly, is found mostly in marketing journals and has been much more inspired by theories and methods from economics and business than from psychology. This line of enquiry is much more pragmatic and directed towards applications of its findings to managerial concerns than the above mentioned psychological stream, as one would expect to see in marketing circles. The interest in consumer behavior for this approach is not direct but derived from the need to investigate and improve marketing strategies. In this case, it is quite common the use of behavioral measures, stemming from several, usually secondary, sources, such as panel and scanner data (i.e., optically scanned data by individual consumers or stores, respectively), rather than verbal reports from consumers. Measures related to brand and product performance have also been frequently used, such as product and brand market share, sales, brand purchases, product stockpiling, price sensitivity, demand elasticity, and such like. Some common independent variables are market variables, such as different types of promotions, distribution, pricing, in-store strategies, assortment, among many others.

From a behavior-analytic point of view, the social-cognitive research does not raise much interest due to its dualistic theoretical tradition and to the type of data they usually collect, based upon verbal reports that supposedly measure cognitive constructs. Marketing research, on the other hand, has produced results based on measures of actual behavior, usually aggregated measures, a practice that brings it closer to behavior analysis. However, due to their primary interest in managerial applications, the field does not work with theoretical frameworks that could explain and interpret consumer behavior.

The proposal of a theoretical framework, based upon concepts derived from "*the scientific study of the individual under optimal conditions of observation"* (Skinner, 1953, p. 334), seems to be a relevant contribution of the BPM to the field of consumer behavior. The model can be used to interpret and integrate findings from the literature. The prediction that consumers maximize informational and utilitarian reinforcement engenders a significant change in the way consumers' choices are to be analyzed. From this point of view, a consumer chooses and acquires products and services but her behavior is influenced by the utilitarian and informational reinforcements, and punishments, produced by these choices. This is learned from a history of association between chosen products and increases (or decreases) in reinforcement and punishment.

With the purpose of illustrating how the BPM can inform the field of consumer behavior, the model was use to investigate the maximization of reinforcement in consumer brand choice. The present research builds upon previous work that adopted the BPM, by testing a variation of the maximization model employed earlier.

The case of brand choice

Brand choice is possibly one of the most pervasive human phenomenon in contemporary industrialized society, where almost any product or service one needs to use has to be chosen among several brand alternatives. For marketing, understanding consumer brand choice is central, for the brand represents the most typical and unique research theme that distinguishes marketing from other sciences (Foxall, Oliveira-Castro & Schrezenmaier, 2007). Moreover, considering the pervasiveness of brand choice, the phenomenon becomes relevant to any scientific approach concerned with the explanation of choice and motivation, as it is the case of behavior analysis.

One significant line of research, developed by Ehrenberg and colleagues using predominantly panel data, has identified several patterns of buying behavior, widely replicated across products and countries (e.g., Ehrenberg, 1972/1988, 1986; Ehrenberg, Hammond, & Goodhardt, 1994; Uncles & Ehrenberg, 1990; Uncles, Ehrenberg, & Hammond, 1995). Ehrenberg (1972/1988) proposed a quantitative model to describe and predict patterns of brand performance. With the model, it is possible to predict, for instance, brand loyalty from information concerning the mean frequency of purchase in the product category and the brand market share. The model assumes that individual consumers (i.e., households) differ in their preferences and that, given individual preferences, their choices across shopping occasions vary *as-if* they were random. It is relevant to note that this line of research has not attempted to identify the variables that might explain individual differences in preference.

Another prolific research tradition in marketing has developed models of brand choice using buying data at the individual level (cf. Russel, 2014). Such models have frequently used random utility frameworks, many of which have been based on multinomial logit models (e.g., McFadden, 1973, Guadagni & Little, 1983; Gupta, 1988; Lattin & Bucklin, 1989) or multinomial probit models (e.g., Hausman & Wise, 1978). A typical characteristic of these models is that consumer's utility for a brand is assumed to be a function of consumer preference for that brand and observable marketing variables, such as price, promotions, and advertising. These models usually include measures of consumer's brand preference obtained from each consumer's previous purchases in the data set, for instance, the level of brand loyalty to brands or to package sizes (Guadagni & Little, 1983; for a review, see Russel, 2014). Models of brand choice have increased in sophistication by exploring new formulae that take into account multiple responses of consumers (e.g., Shin, Misra & Horsky, 2012; Song & Chintagunta, 2006), the influence of marketing endogeneity (e.g., Villas-Boas & Winer, 1999), and structural analyses (cf. Chintagunta & Nair, 2011), to cite just a few developments.

Although these lines of research may generate predictions that are useful to managers, they have not accounted for the variables that influence individual differences in brand preferences (i.e., heterogeneity) or the formation of individual brand repertoires. They have mainly considered that consumers differ with respect to their brand preferences and attempted to predict their behavior based upon their previous consumption patterns (i.e., by including, in the equation, individual parameters of brand loyalty) and changes in marketing variables, such as price and promotions. This type of research does not provide enough basis for theoretical developments concerning why consumers choose the brands they choose. Utility maximization models built from such approach are necessarily limited, considering that they can only assert that consumers maximize the quantity they buy of their preferred brands, without asserting anything about why and how consumers' preferences are formed.

This is where the behavior-analytic emphasis on situational variables and learning processes can be invaluable, for it encourages the search for environmental events that might influence consumer preference and the formation of brand repertoires. The field needs a theoretical framework that points to brand and consumer variables that might influence brand preferences. As previous study has shown (Oliveira-Castro, Cavalcanti & Foxall, 2015) , this can be accomplished by adopting the BPM.

Behavior-analytic maximization model

Previous research based on the BPM, investigating brand choice across routinely purchased supermarket food items, has classified brands according to the level of utilitarian and informational reinforcement they provide. Results have indicated that the patterns of utilitarian and informational reinforcement offered by brands are systematically related to: the quantity consumers buy on each shopping occasion (Foxall, Oliveira-Castro &, Schrezenmaier, 2004; Oliveira-Castro, Foxall & Schrezenmaier, 2005; Oliveira-Castro, Foxall & James, 2008), the allocation of money on brand choice using an adaptation of the matching law (Oliveira-Castro, Foxall &

Wells, 2010), the elasticity of demand of brand choice (Oliveira-Castro, Foxall, Yan & Wells, 2011; Foxall, Yan, Oliveira-Castro & Wells, 2013), the essential value of brands (Oliveira-Castro *et al.*, 2011), and individual differences in brand choice (Cavalcanti, Oliveira-Castro & Foxall, 2013).

In general, these results suggest that the BPM can bridge the existing gap in the literature on brand choice, by pointing to brand characteristics that influence consumers' preferences for different brands. These characteristics could be incorporated in a utility maximization model that would assume that consumers tend to maximize the amount of utilitarian and informational reinforcement they acquire when choosing among brands, by purchasing brands with the highest combination of utilitarian and informational reinforcement within their budget restrictions.

Oliveira-Castro et al. (2015) tested a utility maximization model built upon the BPM. They used a Cobb-Douglas function, one of the most commonly employed in economics (cf. Voorneveld, 2008), due to its analytical tractability, associated to simple well-behaved indifference curves:

$$u : \mathbb{R}_+^n \rightarrow \mathbb{R} \text{ with } u(x) = x_1^{a_1} \cdot \cdot \cdot x_n^{a_n} = \prod_{i=1}^{n} x_i^{a_i} \quad (n \in \mathbb{N}, a_1 \cdot \cdot \cdot, a_n > 0)$$

The authors adapted the function in the following manner:

$$U_{(x1,x2)} = x_1^a \, x_2^b \qquad (1)$$

where U represents utility, x_1 is quantity of utilitarian reinforcement, x_2 is quantity of informational reinforcement, and a and b are empirically obtained parameters.

The two parameters were reduced to one, taking a and b to the $1/a+b$ power (Varian, 2010), which would be equivalent to:

$$a = 1 - b \qquad (2)$$

The budget line for the function is:

$$I = p_1 x_1 + p_2 x_2 \qquad (3)$$

where p_1 and p_2 stand for price of x_1 and x_2 respectively, and I is income.

Maximization of the function will occur when marginal rate of substitution is equal to the slope of the budget line, that is, when:

$$\frac{a}{b}\frac{x_2}{x_1} = \frac{p_1}{p_2} \qquad (4)$$

Information concerning the values of x_1, x_2, p_1 and p_2 were obtained from consumers' purchase data, which made possible the calculation of parameters *a* and *b*.

One of the crucial challenges in calculating the parameters of this type of function is the fact that prices of products and brands are not defined by utilitarian or informational level of reinforcement they offer. Therefore, these prices have to be estimated according to certain procedures. Assuming that product prices increase with increases in the levels of utilitarian and informational reinforcement offered by brands, Oliveira-Castro *et al.* (2015) used a linear regression of price paid per product unit (e.g., 100 g), on each shopping occasion, as a function of the level of utilitarian and informational reinforcement offered by the purchased brands. The ratio of the obtained regression coefficients were then used as *proxies* of the proportion according to which utilitarian and informational reinforcement influence product unit price. Combining this ratio with the equation for the budget line, Equation 3, it was possible to estimate the prices of utilitarian and informational reinforcement paid by each consumer per product unit. After obtaining these price values, the authors combined Equations 2 and 4 to determine the values of *a* and *b* in Equation 1 and calculated the level of utility obtained by each consumer for each product (in different periods). Results showed that Equation

1 fitted well the data, that all parameters were statistically significant and that they were, in general, consistent across time periods for each product category. Individual differences in obtained utility were also consistent across time periods for each product category, indicating that consumers that obtained higher utility levels in one period tended to obtain also higher levels of utility in the other two analyzed time periods and the contrary to those that tended to obtain lower utility levels.

These findings corroborated the interpretation of consumers as maximizing utilitarian and informational reinforcement. Moreover, they raise interesting questions related to the level of utility obtained by consumers. One of them is related to function that the quantity consumers buy of a given product might have in their buying patterns. The calculated utility, in Oliveira-Castro *et al.* (2015), consisted of the level of obtained utilitarian and informational reinforcement per product unit, such as per 100 grams of product. However, it is not difficult to imagine that consumers may obtain the same level of reinforcement per product unit and differ with respect to the total amount of reinforcement they obtain. For example, with equal utility per product unit, one consumer may have obtained 100 grams and the other 200 grams of the product. On the other hand, total utility obtained by two households could be equal if one consumer gets larger quantities of the product with lower utilitarian and informational level than another consumer who gets smaller quantities with higher levels (cf. inter-brand demand elasticity in Oliveira-Castro *et al.*, 2008). Economics and behavior analysis tend to assume that more of a commodity or of a reinforcement is preferred than less of it (cf. Kagel, Battalio & Green, 1995), but in this case qualitative differences, such as the level of reinforcement offered by different brands, might interact with quantity.

In this context of utility maximization of households, it becomes particularly relevant to consider if household economic conditions, such as total income, is related to the level of obtained utility, a hypothesis raised by Oliveira-Castro *et al.* (2015), but not tested with non-purchase data. The present paper, using the same consumer panel data, explores such possibility by examining relations between obtained utility and two demographic variables, social class and age, whose effects upon consumer behavior have been contradictory (cf. Cotes-Torres, Muñoz-Gallego & González-Benito, 2015). By developing a maximization model that measures utility at the household level, a measure sensitive to the quantity bought, and at the level of product unit, a measure not influenced by the quantity consumers buy, the present work investigates whether any of these measures is related to social class and age.

Method

Sample and material

The present study used consumer panel data obtained from AC Nielsen Homescan™, which is a specialized company in providing this kind of data set. The data were collected via barcode scanners installed at the residences of the participants. At the period the data for this research were provided, the sample was randomly selected from a larger data set, which included purchase information from over 10,000 households in Great Britain. The consumer panel was regionally and demographically balanced to represent the household population, and the acquired sample contained information about four product categories during 52 weeks, from July 2004 to July 2005. The product categories were baked beans, biscuits ("cookies" in the US), fruit juice and yellow fats (including margarine, butter and spreads). The number of households (or consumers) selected in each product category was: 1,639 for baked beans; 1,874 for biscuits; 1,542 for fruit juice; and 1,542 for yellow fats. The available data included the following information for each purchase: the brand bought, store, item characteristics, package size, price, weight, total amount spent, number of items purchased, weekly dates and demographic information.

The panel data sample was divided into three consecutive periods of 17, 17 and 18 weeks. Given the purpose of examining utility function for individual households, a criterion of a minimum of five purchases per period was established for each product category, in order to allow for the analysis of repeated measures for each consumer (household). Therefore, data from consumers that showed less than five purchases during each of the three periods were discarded. Consequently, all consumers included in the sample showed at least 15 purchases in a given product category considering the total 52-week period.

In the panel data there was information concerning an average, calculated across the three periods, of 410 consumers and 3,519 purchases per period for baked beans, 1,240 and 24,815 for biscuits, 542 and 6,427 for fruit juice, and 930 and 9,265 for yellow fats, after applying the criterion of five purchases per period. Data analyses were conducted with the aid of Microsoft Excel® and Predictive Analytics Software® (PASW 18).

Procedures and measures for data analysis

The data set was divided into three periods with the purpose of examining the stability of utility function parameters across time and, consequently testing the reliability and robustness of possible findings. In order to obtain the utility function parameters, several measures had to be derived from the panel data. Measures that employed monetary units, such as *income* and *price measures,* were based on British currency (*pence*). The price range for each of the product categories, measured in *unit price* (e.g., price per 100g), was as follows: baked beans, from .0189 to .2100; biscuits from .0620 to 1.7782; fruit juice from .0333 to .5440; and yellow fats from .0456 to .8773.

Utilitarian level. The measure for utilitarian reinforcer was obtained by following the same classification procedure adopted in previous studies (e.g. Cavalcanti *et al*., 2013; Oliveira-Castro *et al*. 2008; Oliveira-Castro *et al*., 2005). Plain or standard formulations of products were ranked as having lower utilitarian levels (utilitarian level equal to 1), whilst products with more sophisticated or alternative formulations were considered as having higher utilitarian level (utilitarian level equal to 2). In the present context, a lower utilitarian level can be exemplified as the standard, plain, formulation of baked beans, whereas the higher utilitarian level for this particular product would be the version with sausage or a diet formulation. Less sophisticated formulations of a product, for example, rich tea biscuits, were ranked as offering lower utilitarian level of reinforcement (equal to 1), whereas more sophisticated formulations, such as chocolate chip biscuits, were ranked as offering a higher level of utilitarian reinforcement (equal to 2). It is important to mention that each product category has its own idiosyncrasies concerning the utilitarian level ranking, which depends on the specific attributes and formulations of each product, but they follow the same general guidelines exemplified above.

***Informational reinforcement level*.** The procedure used to measure the level of informational reinforcement programmed by brands was the same adopted in previous studies (Cavalcanti *et al*., 2013; Oliveira-Castro *et al*., 2008; Oliveira-Castro *et al*., 2010). The procedure was based on a simple questionnaire, where respondents were asked to rate brands in each product category. For each brand listed, consumers were asked to answer the following two questions: (a) Is the brand well known? (0 – Not known at all, 1 – Known a little, 2 – Quite well known, 3 – Very well known); and (b) What is the level of quality of the brand? (0 – Unknown quality, 1 – Low quality, 2 – Medium quality, 3 – High quality). The sample of respondents included consumers living in the UK for most of their lives, selected on a convenience basis and asked to answer one or more questionnaires in October and November 2006. These respondents were not part of the consumer panel. Four questionnaires were used, one for each of the products investigated. Each questionnaire included, for each product, all the brands purchased by the sample of consumers in the panel, after filtering for attributes that are more related to utilitarian reinforcers rather than informational reinforcers. Then, variations of pack sizes and product formulations (e.g., plain baked beans vs. baked beans with sausage; rich tea cookies vs. chocolate chips cookies; plain baked beans vs. organic) by a given brand name were all classified as the same brand. Brand names that belonged to a more general brand but differed with respect to their positioning were classified as different brands (e.g., Asda vs. Asda Smart Price; Tesco vs. Tesco Value). The same group of respondents answered the questionnaires about baked beans (23 respondents), fruit juice (22 respondents), and yellow fats (22 respondents), whereas another group (33 respondents) answered the questionnaire about cookies. The main reason for this separation was the number of brands in each category. The questionnaire for cookies included 315 brands, whereas for baked beans, fruit juice, and yellow fats, the numbers of brands were 45, 99, and 89, respectively. Although the two answers to the questions were expected to be highly correlated, both of them were used because there was the possibility of their existing well-known brands that have low quality (e.g., popularly positioned brands).

In order to obtain one informational level score for each brand, mean score for knowledge and quality was calculated for each respondent and for each brand. The average of these mean values were calculated for each brand across all respondents, referred to as MKQ hereafter. A reliability analysis of MKQ was conducted by randomly assigning questionnaire respondents into two or three (in the case of cookies) groups of approximately equal sizes, whose average MKQ given to each brand were correlated (Pearson) across all brands (N ranged from 45, for baked beans, to 315, for cookies). Correlation coefficients between scores obtained by pairs of groups, three pairs for cookies and one for each of the other products, ranged from .872 to .984, showing acceptable reliability.

Then, based upon this procedure, a value of MKQ was attributed to each brand purchased on each shopping occasion by each consumer in the panel data. For example, Heinz baked beans was given a value of MKQ equal to 2.957, whereas Asda Smartprice baked beans received a MKQ equal to 1.065.

Prices of utilitarian and informational units. Assuming that product prices increase with increases in the levels of utilitarian and informational reinforcement offered by brands, the following equation, adapted from Equation 3, was calculated to identify such relations, using information from the panel data:

$$I_c = p_1\, x_{1_c} + p_2\, x_{2_c} \qquad (5)$$

where I_c refers to the total amount spent by a given consumer across all shopping occasions of a given period of 17 weeks, a *proxy* of *purchase income*, x_{1c} and x_{2c} stand for the sum, across shopping occasions, of utilitarian and informational reinforcement, respectively, purchased by each consumer (or household) during a given 17-week period. The values of x_{1c} were obtained with the following formula:

$$x_{1_c} = \sum_{i=1}^{n} UTI_{ci} \qquad (6)$$

where UTI_{ci} refers to the level of utilitarian reinforcement of brands bought by each consumer (subscript *c*) on each shopping occasion (subscript *i*). Then, Equation 6 was calculated across all shopping occasions of a given consumer, for each period and for each product. The values of x_{2c}, that is, the total amount of informational reinforcement, were calculated analogously with the use of the following equation:

$$x_{2_c} = \sum_{i=1}^{n} INF_{ci} \qquad (7)$$

Therefore, after calculating the values of I_c, x_{1c} and x_{2c}, prices of utilitarian and informational reinforcement, p_1 and p_2 in Equation 5, were calculated with the use of a linear multiple regression where I_c was a linear function of x_{1c} and x_{2c}. These price values were obtained, with data across consumers, for each period of each product category.

Parameters of the utility function. These values of x_{1c}, x_{2c}, p_1 and p_2 were then used to calculate the parameters of the utility function from Equation 4. This was done by using a linear regression, calculated across consumers within a given period, where x_{2c} was a function of $[(x_{1c}*p_1)/ p_2]$. The slope of this linear regression was equal to b/a. Combining this value of the slope with Equation 2 (i.e., $a = 1 - b$), it was possible to obtain the values of *a* and *b*, for each period of each product category.

Social class and age. Information concerning social class and age (household member that participates in the panel) were available in the original dataset, where social class was obtained from the classification of Social Grade, generated by the

National Readership Survey (NRS) in 2015 (cf. National Readership Survey, 2015). Social grade is a classification system based on occupation, developed for use on the NRS, and for over 50 years NRS has been the research industry's source of social grade data. The classifications, based on interviews of chief income earner in each household, are as follows: *A - Higher managerial, administrative and professional; B - Intermediate managerial, administrative and professional*; *C1 - Supervisory, clerical and junior managerial, administrative and professional;C2 - Skilled manual workers*; *D - Semi-skilled and unskilled manual workers*; and *E - State pensioners, casual and lowest grade workers, unemployed with state benefits only*. In the available dataset, categories A and B were collapsed into AB. The classification system does not include income, but shows a strong positive correlation with it (cf. National Readership Survey - NRS, 2015).

Results

Table 1 shows the values of p_1, p_2, R^2, *F-ratio* and *N* (number of consumers/households), for each period from each product, obtained using Equation 5. All parameters were significant and values of R^2 ranged from .47 to .83. Smaller values were observed for *baked beans*, which was the product category with the lowest number of purchases. Values of p_1 and p_2 were relatively similar across time periods for each product. With the exception of the values for the 1st period for baked beans and 2nd period for biscuits, all ratios between p_1 and p_2 (i.e., p_1/ p_2) were in the same direction, that is, larger or smaller than 1.00, with little variation in value. This ratio varied from 1.00 to 1.56, 0.60 to 1.72, 0.25 to 0.72 and 0.72 to 0.89, for baked beans, biscuits, fruit juice and yellow fats, respectively.

Table 1 also shows the values of Equation 4 parameters, including *a*, *b*, r^2, *F-ratio* and *N*, which were calculated using a linear regression, with data from all consumers for each period of each product. Parameters *a* and *b* were obtained by combining Equations 4 and 2.

As can be observed in the table, Equation 4 fitted the data reasonably well, with r^2 ranging from .34 to .90, and all obtained parameters were statistically significant. The largest and lowest values of r^2 were obtained for biscuits and baked beans, which showed the largest and smallest number of data points (*N*), respectively. With the exception of the values of *a* and *b* obtained for baked beans on the 1st period and for biscuits on the 2nd period, all other values of the parameters showed a consistent tendency, that is, *a* was larger than *b* for the three periods or *b* was larger than *a* for the three periods. For baked beans, *a* was consistently larger than *b* for the 2nd and 3rd periods, showing similar values. In the 1st period, the values of *a* and *b* were almost identical. For biscuits, *a* was larger than *b* on the 1st and 3rd periods, but it was smaller than *b* on the 2nd period.

Having the values of *a*, *b*, x_{1c} and x_{2c}, Equation 1 was used to calculate the level of total utility obtained by each household purchasing each product during each time period. Table 1 shows the average and standard deviation of the level of utility, calculated across households, during each period for each product.

As shown in the table, average utility differed across products and were very similar across time periods of the same product. One-way analyses of variance (Anova) were conducted comparing the average utility across products for each time period. The main effects of the Anova showed that the average utility differed significantly across products in the 1st ($F_{(3,2992)}$= 258.65, p < .000), 2nd ($F_{(3,3149)}$= 280.27, p < .000) and 3rd

($F_{(3,3215)}$= 290.91, p < .000) periods. *Post-hoc* tests (Tukey HSD) revealed that significant differences in average utility, in all three time periods, were systematically ordered: mean utility for biscuits was larger than for all other products; mean for fruit juice was larger than for baked beans, but did not differ from yellow fats ; and mean utility for yellow fats did not differ from that obtained for baked beans.

It can also be observed from Table 1 that average utility was very similar across time periods of the same product category. The largest difference in average utility was observed between the 2nd and 3rd periods for biscuits and it was equal to 2.79 (8.75% of the smaller value).

Calculating the total utility level obtained by each household in each period for each product allows for the examination of the stability and consistency, across time, of individual differences in terms of utility. In order to do so, statistical correlations (Spearman) between utility levels obtained by the same household in different time periods were calculated. This yielded three different correlation coefficients for each product category (i.e., 1st period *versus* 2nd period, 2nd *versus* 3rd, and 3rd *versus* 1st) which are shown in Table 2. All correlation coefficients were significant and positive, indicating relatively stable individual differences in obtained utility across time. Coefficient values varied from .59 to .91, with 9 out of 12 values above .75, indicating moderate to strong relations.

In order to calculate obtained utility per product unit, x_{1c} and x_{2c} in Equation 1 were replaced by the averages, weighted by product quantity, of utilitarian and informational reinforcement offered by purchased brands, calculated across all shopping occasions for each household (cf. Equations 8 and 9 in Oliveira-Castro *et al.*, 2015). The values of parameters *a* and *b* were those shown in Table 1. The non-parametric correlation coefficients(Spearman) between total household utility and utility per product unit, calculated across households for each period of each product, were all positive and significant, ranging from .58 to .61, .24 to .30, .34 to .51 and .42 to .44, for baked beans, biscuits, fruit juice and yellow fats, respectively. These indicate that households that tend to obtain higher total utility also tend to obtain higher utility per product unit, although the moderate size of the coefficients suggests that this relation is not strong.

Correlation coefficients (Spearman) between social grade and utility per product unit, also calculated across households for each period of each product, showed that, with the exception of two periods for biscuits, they were all significant and positive, ranging from .16 to .17, .03 to .13, .19 to .24 and .08 to .13, for baked beans, biscuits, fruit juice and yellow fats, respectively. These indicate that household classified in higher social classes tend to obtain significantly higher utility per product unit, although the low coefficient values suggest weak relations between the variables. None of the coefficients were significant for the correlations between social class and total household utility, or those between age and the two utility measures.

Discussion

The main purpose of the present paper was to develop and test a variation of the utility model presented by Oliveira-Castro *et al.* (2015), which calculates the level of total utility obtained by households during a given period and the level of obtained utility per product unit, and to examine the relations of these two utility measures to social class and age. Results indicated that the proposed model variation (Equations 1 to 4) fitted well consumers' brand choice data, similarly to the model presented by Oliveira-Castro *et al.* (2015).

The values of r^2, for Equation 4, were equal or higher than .60, except for baked beans, for which values ranged from .34 to .43. Parameters obtained for Equation 4 were all statistically significant. Moreover, in 10 out of 12 comparisons, the values of parameters a and b (Equation 1) were consistent for the same product, that is, they showed very similar values and similar proportions (*i.e.*, a always larger or always smaller than b) across periods for a given product (Table 1).

Product prices were estimated under the assumption that shelf price is a direct function of utilitarian and informational reinforcement programmed by the products (Equation 5). All equation parameters (p_1 and p_2) were significant and values of R^2 were above .47, showing variation across products. The lowest R^2 was found for baked beans, which also has the smallest number of brands and data points (i.e., purchases), which could help explain lower values of R^2. These price parameters (p_1 and p_2), obtained from individually aggregated data, that is, from all shopping occasions for each consumer during a given time period, were then used to estimate the parameters of the utility function. Considering, however, that prices vary with changes in other factors, in addition to informational and utilitarian levels of reinforcement offered by brands, such as store brand, store location, packages, and so on, these price estimates are oversimplified *proxies* of informational and utilitarian prices as they appear in the market. Variables not included in the estimation of such prices may help explain the two, out of twelve cases, above-mentioned reversions observed in price parameters. Estimates of informational and utilitarian prices based upon individual consumers' patterns of purchases might yield more realistic pricing measures, although they would require larger sets of panel data.

The proportion of utility level associated to utilitarian and informational reinforcement offered by different brands was consistent for each product across time periods (with the exception of one period for baked beans and one for biscuits, as discussed above). Having these parameters, *a* and *b*, it was possible to measure, for each product category, the importance or weight of utilitarian and informational reinforcement for consumers. For example, as one can see on Table 1, for baked beans and biscuits, utilitarian is more important than informational in the sense that consumers get more utility from utilitarian than informational (*a* is larger than *b*). For fruit juice and yellow fats, this relation is reversed, with informational being more relevant than utilitarian.

Knowing the proportion of utility obtained by each group of attributes, utilitarian or informational, would be much useful to several marketing strategic decisions. For example, in defining brand assortment, retail managers should attempt to offer brands with higher levels of the attribute most valued by consumers in each product category.

In the case of manufacturers, attributes of products and brands should take into consideration the manner according to which consumers maximize utility in each category. When introducing innovations in a given market category managers should consider if consumers, in such market, give more weight to informational or utilitarian reinforcement. In the case of baked beans and biscuits, for example, manufacturers should give more attention to utilitarian than to informational attributes, innovating in terms of product attributes, whereas, for fruit juice and yellow fats, brand differentiation might be a better strategy, considering that more utility is obtained from informational reinforcement.

Having determined Equation 1 parameters, *a* and *b*, it was possible to calculate the level of utility obtained by each consumer and, consequently, the average utility obtained by buying each product, across consumers (Table 1). This average product utility was calculated for each period and results showed that it was specific to each product and differed, in some cases, significantly from the average utility observed for other products. Moreover, the average utility for each product was very similar for the same product across time periods. These results revealed that utility level is specific to each product consumers buy. In the present case, utility is, in average, higher for biscuits than for all other products, and higher for fruit juice than for baked beans. Average utility for yellow fats did not differ significantly than that obtained for fruit juice and baked beans. This kind of information may help explain consumers' purchase patterns across product categories, particularly if combined with other behavioral-economic measures, such as price elasticity of demand or brand essential values (e.g., Foxall *et al.* 2013; Oliveira-Castro *et al.* 2011).

The present results also revealed that individual differences in utility are consistent and stable across time, that is, consumers that tend to obtain higher levels of utility in one time period tend to do the same in other time periods, whereas those obtaining low levels of utility in one period continue to do so in other periods. Oliveira-Castro *et al.* (2015) raised the possibility that such individual differences in utility are, most likely, associated to their available budget, for products offering higher levels of utilitarian and informational reinforcement are usually more expensive than those offering lower levels of them (Equation 5). Assuming that consumers maximize informational and utilitarian reinforcement and that their income are stable across time periods, this is to be expected. Higher incomes would be associated to higher budget lines and, consequently, to the possibility of consuming commodity bundles located at higher indifference curves (i.e., higher quantities of the two commodities) (cf. Varian, 2010). These are trivial predictions in the light of microeconomic consumer demand theory. What is new in the present approach is that the *commodities* examined are utilitarian and informational reinforcement offered by brands of products. In other words, consumers choose between baked beans and biscuits, as widely discussed in microeconomic theory, but they also choose between bundles of utilitarian and informational reinforcement offered by different brands of baked beans, when purchasing baked beans.

In general, the findings replicate those reported by Oliveira-Castro *et al.* (2015), which demonstrates that similar results can be obtained by either maximization model and corroborating the interpretation that consumers maximize utilitarian and informational reinforcement, as can be predicted by the BPM. The advantage of the model presented here is therefore based upon the possibility of producing two measures of utility, a total household utility and a utility per product unit. Whether such utility measures are functionally different, in the sense of being influenced by different variables, is an empirical question that the present work just began to answer.

The positively significant, but weak, correlations between the two utility measures, calculated across households, favors an interpretation that they share some functional similarity but differ in important aspects. Additionally, the finding that utility per product unit, but not total household utility, was correlated to social class corroborates further the interpretation that these two measures are indeed functionally different. Moreover, considering that social class shows a strong positive correlation to total household income (cf. NRS, 2015), these results indicate that, at least for routinely purchased food items: a) higher household income is associated to higher levels of reinforcement per product unit consumed, but not necessarily to the absolute amount of reinforcement obtained per household; b) there seems to be no equivalence, in terms of utility, between buying larger quantities of products with lower level of reinforcement and buying smaller quantities of products with higher level of reinforcement; and c) information concerning the number of persons in each household, unfortunately not available in the present dataset, might be useful for clarifying the relations between household income, utility and quantity of purchased product.

The present results bring additional support to previous work that indicated that brand repertoires of consumers are composed of brands that offer similar levels of utilitarian and informational reinforcement (e.g., Foxall *et al.*, 2004), which, in turn, suggests that individual differences in brand choice are related to such choice patterns (e.g., Oliveira-Castro *et al.*, 2015), which seem related to household income level. These tentative conclusions might contribute to fill in the existing knowledge gap in the literature, concerning consumers' brand preferences, demonstrating, once more, the potential usefulness of a behavior-analytic approach to consumer behavior, as proposed by the BPM.

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