

Consumer brand choice: Money allocation as a function of brand reinforcing attributes.

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Abstract

Previous applications of the matching law to the analysis of consumer brand choice have shown that the amount of money spent purchasing a favorite brand tends to match the quantity bought of the favorite brand divided by the quantity bought of all other brands. Although these results suggest matching between spending and purchased quantity, branded goods differ qualitatively among themselves rendering previous matching analyses incomplete. Consumer data panel, obtained from a commercial firm, containing information about more than 1,500 British consumers purchasing four grocery product categories (baked beans, biscuits, fruit juice and yellow fats) during 52 weeks, were used. All the brands purchased were classified according to the level of informational and utilitarian reinforcement they were programmed to offer. An adaptation of the generalized matching law was adopted, in which the amount of money spent was a power function of the quantity bought, informational level of the brand bought, utilitarian level of the brand bought, and a measure of price promotion.

Consumer brand choice:

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Knowledge concerning when, what and how much consumers buy is crucial for well-grounded marketing strategies (Gupta, 1988). In the case of routinely purchased products, a considerable amount of research has been dedicated to the investigation of consumer brand choice, which has revealed some characteristics of consumers' patterns of consumption. Few consumers are completely loyal to one brand of frequently-purchased products during a period of one year and that most consumers have a repertoire of brands, composed of a subset of brands offered in the product category, from which they buy mostly. These findings stemmed from investigations based upon consumer panel data and have been replicated across dozens of product and service categories in several countries (cf., Ehrenberg, 1972; 1988; Ehrenberg, Uncles & Goodhardt, 2004; Uncles, Ehrenberg & Hammond, 1995). Consumer panel data provide information about the purchases that individual consumers make during a given period of time. It may include, for example, all food grocery purchases of a number of individuals during several weeks or months.

The Matching Law

Another line of research, based on conceptual and methodological tools derived from behavioral economics and behavioral psychology, has found that brands that form consumers' brand repertoires function as substitutes. Such investigation has been inspired by the matching law (Herrnstein, 1970), which states that, in choice situations, the distribution of behavior among alternatives matches the distribution of reinforcers obtained from these alternatives. The matching law was initially based on investigations of nonhuman performance in the laboratory, most of which used pairs of variable-interval concurrent schedules (i.e., simultaneously available variable-interval reinforcement schedules). In typical experiments, the rate of reinforcement (e.g., food interval-schedule) of both alternatives is

manipulated systematically across several experimental conditions. So, for example, in one condition Alternative 1 may program 33% of total number of reinforcers available during one hour, whereas Alternative 2 may program the remaining 67%. In a second condition the percentages may be reversed, that is, Alternative 1 may offer 67% of reinforcers whereas Alternative 2 offers only 33%. The matching law predicts that the distribution of responses on Alternatives 1 and 2, across several conditions, will match the proportion of reinforcement obtained in the two alternatives. The mathematical formulation of the matching law, proposed by Herrnstein (1970), is:

$$\frac{P_1}{P_1 + P_2} = \frac{R_1}{R_1 + R_2} \quad (1)$$

where P and R represent responses and reinforcers, respectively, and subscripts indicate the concurrent alternatives. Assuming that there could be deviations from the perfect matching relation, Baum (1974, 1979) proposed the generalized matching law, which is presented below:

$$\frac{P_1}{P_2} = b \left(\frac{R_1}{R_2} \right)^s \quad (2)$$

where b and s are empirically obtained parameters which measure the level of bias between the alternatives and the sensitivity to reinforcer distribution, respectively.

When b and s are equal to one, *Equation 2* is equivalent to *Equation 1*. According to Baum, the parameter b should deviate from unity when there are sources of bias in the situation, as when one operandum is easier to operate than the other. In this case, a constant preference towards one of the alternatives would be expected, which is called *bias*. The parameter s would be larger than unity when there is a preference, above the matching relation, for the alternatives that offer higher rates of reinforcement, and is called *overmatching*. It would be lower than one when there is a preference, below the matching

relation, for the alternatives programming lower reinforcement rates, called *undermatching* (cf. Baum, 1974,1979).

This theoretical framework has been adopted to analyze a wide variety of choice situations, both with human and nonhuman subjects, inside and outside the laboratory (e.g., Pierce & Epling, 1983; Redmon & Lockwood, 1986). The matching law has also been used in behavioral economics, where it has been suggested that s can be used as a measure of substitutability between the reinforcers available in the choice situation (e.g., Kagel, Battalio & Green, 1995). When the exponent is equal to one, changes in reinforcement ratio are followed by proportional changes in response ratio, and commodities can be interpreted as perfect substitutes, as it is the case when both alternatives offer the same reinforcer. Almost all empirical investigations involving the matching law have programmed identical reinforcers in both alternatives.

The Matching Law and Brand Choice

Considering that the matching law can be used to measure the level of substitutability of reinforcers, Foxall (1999) proposed its extension to the analysis of consumers' brand choice, as a way of measuring the level of substitutability of brands. However, several adaptations would have to be made in order to apply the matching law to brand choices occurring in real retail environments. Subsequent empirical work illustrated the necessary adaptations using small and large samples of consumer panel data (Foxall & James, 2001; Foxall, Oliveira-Castro & Schrezenmaier, 2004). One of the necessary adaptations is related to the fact that choices in retail environments are more similar to ratio schedules than to interval schedules, where the amount of money paid (response) would be a function of the amount the person obtains (reinforcement) (cf. Foxall, 1999). Another necessary adaptation concerns the number of simultaneously available alternatives, which in retail environments usually involve several different brands, whereas in the typical laboratory experiment only

two sources of reinforcement are provided. The above mentioned authors adapted the matching law by calculating response and reinforcement ratios with respect to the brand each consumer bought most frequently during the entire period of analysis (the *preferred* brand). Therefore, response ratios were obtained by dividing the amount each consumer paid for his or her preferred brand divided by the amount paid for all other brands the consumer bought during the period. The first empirical results, using a small convenience sample of consumers, showed that the value of the exponent s was closer to one for products that would be expected to function as substitutes (e.g., butter and margarine) than those expected to be complementary or independent brands or products (cf. Foxall & James, 2001). Subsequent research, using a larger sample, also found exponents close to unity for brands belonging to an individual consumer's repertoire (Foxall et al., 2004).

Although these results suggest matching between spending and purchased quantity, branded goods differ qualitatively among themselves rendering previous matching analyses incomplete. Brands in a product category are not all identical. As a matter of fact, most part of marketing strategies are directed towards differentiating one brand from the others, through innovation, advertising, promotions, and so on. Therefore, the analysis of brand choice would be much enriched if it could take into consideration the quantitative and qualitative reinforcing value of brands.

Qualitative Differences Across Brands

A theoretically systematic analysis of qualitative differences across brands has been advanced by another, related, line of investigation, which has attempted to elucidate some of the variables that influence the formation of consumers' brand repertoires. This research derived from the Behavioral Perspective Model (BPM), which consists of a behavioral theoretical framework developed to interpret and explain consumer behavior (cf. Foxall, 1987; 1990; 1998). According to the BPM, consumer behavior occurs at the intersection of a

consumer-behavior setting and the individual's learning history of consumption, and is a function of utilitarian and informational consequences. The setting contains events in the consumption environment that function as discriminative stimuli, signaling the different consequences for different consumer responses. Consumer responses may produce three types of consequences, namely, utilitarian reinforcement, informational reinforcement, or aversive consequences. Utilitarian reinforcement consists of practical outcomes of purchase and consumption, derived from the use of the product itself. This is related to the functional outcomes, to the value-in-use of a product or service. Informational reinforcement, by contrast, is symbolic, social, mediated by the actions and reactions of other people. In this sense, informational reinforcement is similar to Skinner's (1957) conception of social behavior, more akin to exchange value. It consists of feedback on the performance of the individual as consumer. Whereas utilitarian benefit is related to economic and functional reinforcing value of products or services, informational reinforcement is related to social status and prestige, associated to buying, owning, or using products or services. In addition to these two types of reinforcing consequences, consumer responses also produce aversive consequences, such as spending money and time when searching and buying. Thus, according to this interpretation, the probability of purchase and consumption depends on the relative weight of the reinforcing and aversive consequences that are signaled by the elements in the consumer behavior setting (cf. Alhadef, 1982).

Based on this distinction between utilitarian and informational benefits, Foxall and colleagues (e.g., Foxall et al., 2004; Oliveira-Castro, Foxall & Schrezenmaier, 2005) classified all the brands included in a panel data according to the level of programmed utilitarian and informational reinforcement that they offered. The sample contained information about purchases of nine grocery food products made by 80 consumers during 16 weeks. Brands in each product category were ranked according to a two-point scale of

programmed utilitarian reinforcement, such as baked beans with sausage *versus* plain baked beans, which was based on the analysis of product attributes. Brands were also ranked according to a three-point scale of programmed informational reinforcement, which was based on an analysis of brand positioning, such as good-value-for-money own brands, higher-level own and lower-level national brands, and higher-level national brands. Brand average prices were considered in distinguishing lower- and higher-level national brands. This type of analysis showed that the majority of consumers make most of their purchases within brands belonging to the same level of utilitarian and informational reinforcement, suggesting that consumers' brand repertoire are formed on the basis of reinforcement level offered by the brands (cf. Foxall et al., 2004). Moreover, this brand classification produced some interesting findings concerning inter- and intra-brand (cf. Oliveira-Castro et al., 2005) and inter- and intra-consumer elasticities of demand (cf. Oliveira-Castro et al., 2006), indicating that consumers respond to changes in informational, utilitarian and aversive consequences, by changing the quantity they buy.

The separation of utilitarian, informational and aversive consequences may give support to a more complete model of consumer brand choice, one which incorporates both quantitative and qualitative reinforcing effects of brands. The main purpose of the present paper is to propose and test such model, by combining the matching law analysis of brand choice with the types of consequences (utilitarian, informational and aversive) proposed by the BPM.

Proposed Model

One way of combining these two lines of research is to analyze how consumers allocate the amount of money they spend as a function of what they obtain in terms of brand quantity, utilitarian reinforcement, informational reinforcement and price. Using the usual

representation of the matching law that includes two choice alternatives, the model could be represented as:

$$\frac{S_1}{S_2} = \left[\left(\frac{Q_1}{Q_2} \right)^{s_1} \left(\frac{U_1}{U_2} \right)^{s_2} \left(\frac{I_1}{I_2} \right)^{s_3} \left(\frac{P_1}{P_2} \right)^{s_4} \right]^c \quad (3)$$

where S , Q , U , I and P represent amount spent, quantity bought, utilitarian level of brand bought, informational level of brand bought, and price, respectively. Subscripts 1 and 2 represent the two alternative brands, and s_1 , s_2 , s_3 and s_4 are empirically obtained parameters that can be interpreted as measures of sensitivity to each type of reinforcement attribute. Parameter c can be interpreted as a measure of bias in favor of one of the brands when all reinforcing attributes are identical between the two brands (i.e., all reinforcement ratios are equal to one). Equation 3 could be used to measure consumers' sensitivity to different reinforcing attributes offered by different brands. This type of equation might serve to test if consumers do respond to these reinforcing attributes and, if they do, what is their order of importance in determining brand choice of routinely-purchased products.

In practice, Equation 3 is difficult to apply in real retail environments because there are usually many different brands to choose from, each one of which in different package sizes and, consequently, different prices. The adaptations adopted in previous works, where information concerning the preferred brand was used as the numerator of the ratios and information relative to all other purchased brands formed the denominator (e.g., Foxall & James, 2001; Foxall et al., 2004), pose problems for some of the measures used in the equation. The adaptations seem to be applicable to the ratios of amount spent and quantity, for which it is possible to divide the amount spent (or bought) of the preferred brand by the amount spent (or bought) of all other brands, during a given period of time (each shopping trip, every three weeks, or such like). However, these same adaptations cannot be applied to the other variables in the same manner. In the case of utilitarian ratio, it would not make

sense to divide, for example, the utilitarian reinforcement level of the preferred brand (e.g., a value equal to 1 or 2) by the utilitarian reinforcement level of all other brands. The utilitarian level of all other brands purchased by the consumer cannot be simply added, as amount spent and quantity can. The denominator would have to be calculated using some reductive measure, such as the average value of utilitarian level of all other brands. The same reasoning applies to the case of informational and price ratios, for which an averaging procedure, or something like it, would need to be used. If this averaging procedure were to be adopted for some of the variables, and not for the others, equation parameters may not be compared with each other.

Another possible way to adapt Equation 3 to real purchases situations would be to measure how the amount spent on a given shopping occasion changes in relation to each consumer's typical spending as a function of changes in each alternative's reinforcing attributes (quantity, informational, utilitarian, price), also relative to typical attributes the consumer buys. Typical spending could be measured, for example, by the average amount each consumer spent during the entire period. This average could be used to divide the amount spent on each shopping occasion, which would yield a relative measure of spending anchored by the typical spending of each consumer. Analogous relative measures could be adopted for reinforcing attributes, that is, each of them could be divided by the average obtained for each consumer during the period. The adoption of relative measures would also make data from individual consumers comparable, for all changes in amount spent, quantity bought, and so on, would be relative to each consumer's own average (cf. Oliveira-Castro et al., 2005, 2006). The use of relative measures would provide an assessment of changes in spending, relative to typical spending, as a function of changes in reinforcement attributes, relative to typically obtained attributes. This proposal could be represented as follows:

$$\frac{S_t}{\bar{S}} = \left(\frac{Q_t}{\bar{Q}} \right) \left(\frac{J_t}{\bar{J}} \right) \left(\frac{I_t}{\bar{I}} \right) \left(\frac{\bar{P}}{P_t} \right) \quad (4)$$

The subscript t represents each shopping occasion. All denominators, with the exception of that for price, are averages calculated across all purchases of each consumer. In the case of the price ratio, the average is calculated across all purchases that each consumer made of the brand that is being purchased on the t^{th} shopping occasion. The price ratio was here reversed with the purpose of transforming this variable into a measure of depth of price promotion. Other parameters can be interpreted as in Equation 3, with the exception of k , which can be interpreted as a measure of bias towards spending more or less the average amount spent when all reinforcing attributes are equal to their average values. According to Equation 4, if a consumer buys the same quantity of the same brand in the same package size on every shopping trip, amount spent would vary only with changes in price, for all other ratios would be eliminated from the equation because they would be equal to one. However, considering that few consumers, approximately ten percent, of routinely-purchased products are exclusive buyers of one brand during a period of one year, that is, most consumers purchase several brands during this period (cf. Ehrenberg et al., 2004), all ratios in the equation should show some variation in their values for the vast majority of consumers.

Method

Sample and Procedures. Consumer panel data were obtained from ACNielsen HomescanTM which, at the period of this research, included data from over 10,000 households in Great Britain who used home barcode scanners. The panel was regionally and demographically balanced to represent the household population. The data set used included information about four product categories during 52 weeks from July 2004 to July 2005. The four products were baked beans, cookies, fruit juice, and yellow fats (including margarine, butter and spreads), for which there were data about the purchases of 1,639, 1,874, 1,542 and

1,817 randomly selected households, respectively. With the purpose of excluding extreme light buyers from the samples, data from consumers who purchased less than seven times in the product category during the 52-week period were excluded. The edited samples contained information about 832, 1,594, 895 and 1,354 households purchasing respectively, baked beans, cookies, fruit juice and yellow fats. These households were responsible for 81.67%, 98.99%, 92.32% and 95.00% of the total quantity purchased during the 52-week period in the categories, respectively. The total number of data points, that is, number of households multiplied by number of purchases they made, was equal to 13,729 purchases for baked beans, 75,847 for cookies, 21,400 for fruit juice, and 30,906 for yellow fats. For each purchase, the data included information about the brand, store, item characteristics, package size, total amount spent, number of items, and weekly date.

The level of informational benefit offered by each brand was measured with the use of 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: 1) Is the brand well known? (0 - Not known at all, 1- Known a little, 2 - Quite well known, 3 - Very well known); and 2) What is the level of quality of the brand? (0 - Unknown quality, 1 - Low quality, 2 - Medium quality, 3 - High quality). Small sample of consumers who were living in the UK for most of their lives were selected on a convenience basis and asked to answer one or more questionnaires. 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 benefits rather than informational benefits. Then, different pack sizes and different product formulations (e.g., plain baked beans vs. baked beans with sausage; rich tea cookies vs. chocolate chips cookies; plain baked beans vs. organic) 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 consumers 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. Data were collected in October and November 2006. Although the two answers to the questions were expected to be highly correlated, both of them were used because there was the possibility of there 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 consumer and for each brand. The average of these mean values when then calculated for each brand across all consumers, 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 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 $r = .872$ to $.984$, showing acceptable reliability.

In the marketing context of routinely-bought supermarket food products, higher levels of utilitarian benefit can be identified by the addition of (supposedly) desirable attributes. These attributes are considered to have value-adding qualities for the product or its consumption, they are visibly declared on the package or are part of the product name, and ultimately justify higher prices. Moreover, in most cases, several general brands offer product varieties with and without these attributes. In the present work, utilitarian level of items was

assessed by adopting the same ranking procedure used in previous studies (cf. Foxall et al., 2004; Oliveira-Castro et al., 2005). Plain formulations of items were ranked as having lower utilitarian levels (utilitarian value equal to 1), whereas more sophisticated formulations were ranked as having higher utilitarian level (utilitarian value equal to 2). Sophisticated formulations included additional attributes (e.g., plain baked beans vs. baked beans with sausage) and/or differentiated types of products (e.g., plain cookies vs. chocolate chip cookies). In the case of differentiated product types, several manufacturers tend to offer the different product types at differentiated prices (e.g., plain cookies were cheaper than more elaborate cookies for all brands examined).

Results

Table 1 shows Equation 4 parameters, calculated using data from each of the four product categories. Parameters were calculated using data from each shopping occasion for each consumer. It should be noted that, in many cases, consumers bought more than one brand and/or type of package on one shopping occasion. This was more common in the case of products like biscuits, where consumers usually buy more than one type per shopping trip, and less so in the case of products such as baked beans. Results presented in Table 1, shown on the left-hand column, considered purchase of each different brand and/or package by each consumer as a different data point, that is, n was equivalent to each different purchase on each shopping occasion by each consumer for each product.

As can be seen in the left-hand column in Table 1, all multiple regressions were significant (.05) and R^2 values ranged from .207, for cookies, to .755, for baked beans. The number of data points (n) used to calculate each regression ranged from 13,713 for baked beans to 74,234 for cookies. Values of $\text{Log}_n k$ were very close to zero and ranged from -0.07 to 0.04, indicating the absence of strong bias when reinforcing attributes were relatively constant. Parameters s_1 to s_4 were all significant for all product categories, suggesting that

consumers respond to all the reinforcing attributes included in the equation. Values of s_1 , s_2 and s_3 were all positive (with the exception s_3 for cookies), indicating that increases in quantity, utilitarian and informational reinforcement were associated with increases in spending. The values of s_3 for cookies were equal to -0.01, which indicates that informational reinforcement has little influence on amount of spending for cookies. Values of s_4 were all negative, indicating that increases in depth of price promotions are significantly related to decreases in spending. The magnitude of Equation 4 parameters shows that, for all products, s_4 was larger than s_1 , s_1 was larger than s_2 , and s_2 was larger than s_3 , indicating that changes in spending were associated to changes in price promotion, quantity bought, utilitarian brand level and informational brand level, in that order of importance. The only exception to this occurred for baked beans, for which s_4 was equal to s_1 .

The data presented above were based on the analysis of each purchase on each shopping trip by each consumer. In terms of choice of money allocation, one might argue that purchases made on the same shopping trip would not be necessarily competing against one another for consumers may allocate their money to different reinforcing attributes across combinations of different brands and/or package sizes on the same shopping occasion. Two different types of cookies (e.g., chocolate-chip cookies and savory biscuits), for example, may be purchased on the same shopping trip and could function more as complements than substitutes. In this case, money allocation could average out reinforcing attributes and the results presented in the left-hand column Table 1 might be a misleading picture of consumers' choice sensitivity to reinforcement attributes. With the purpose of testing such possibility, Equation 4 parameters were calculated by using weekly data for each consumer. Each data point was obtained by calculating the average value for each week for each consumer, divided by the average value obtained with all data points. For example, average amount spent per week by a given consumer was divided by the average amount this same

consumer spent across all purchases. The other variables were calculated analogously. The right-hand column in Table 1 shows Equation 4 parameters, obtained with weekly data for each consumer and for each product category.

As can be seen in the right-hand column of the table, results were very similar to those obtained with all data points. All multiple regressions were significant ($p < .05$) and R^2 values ranged from .227, for cookies, to .775, for baked beans. The number of data points (n) used to calculate each regression ranged from 11,666 for baked beans to 32,452 for cookies. Values of $\text{Log}_n k$ were very close to zero and ranged from -0.05 to 0.03. Parameters s_1 to s_4 were all significant for all product categories. Values of s_1 , s_2 and s_3 were all positive, and values of s_4 were all negative. The magnitude of these parameters shows that, for all products, s_4 was larger than s_1 , s_1 was larger than s_2 , and s_2 was larger than s_3 .

The reduction in the number of data points for the regressions using weekly data indicates the tendency of consumers to buy more than one brand and/or package size per shopping trip. This tendency was stronger for cookies, where weekly data point number (32,452) was less than half the total number of data points (74,324), and less evident for baked beans for which data points reduced less than ten percent (13,713 to 11,666). The values of R^2 were larger for the regressions with weekly data than for the ones with all data points for all product categories.

Discussion

Consumers' spending changed systematically with changes in price promotion, quantity bought, utilitarian reinforcement and informational reinforcement, in decreasing order of importance. Increases in price promotion were associated with decreases in spending, whereas increases in the other variables were associated with increases in spending. These findings were replicated across all four products and two types of analyses.

The observed positive relations between spending and quantity bought, utilitarian and informational reinforcement levels, demonstrate that these all function as positive reinforcers. In the case of depth of price promotion, the negative relations indicate that increases in the relative price consumers find inevitably increases the amount they spend. This does not mean, of course, that price functions as positive reinforcer, but rather that it functions as an inevitable aversive event. This latter interpretation is confirmed by results from analyses of demand elasticity, which demonstrate that increases in price decrease the amount consumers buy (cf. Oliveira-Castro et al., 2005). The observed magnitudes of Equation 4 parameters also indicate that changes in prices, away from typical prices, are the main source of influence upon changes in consumers' spending.

The observed magnitudes of the other parameters suggest some interesting patterns of consumer brand choice. They indicate that consumers increase the amount they spend across shopping occasions, relative to their usual spending, mainly in order to get larger quantities of a given product. This finding questions the supposition that the quantity consumers buy remains relatively constant across shopping occasions (cf. Bell, Chiang, & Padmanabhan, 1999; Ehrenberg, 1972/1988; Gupta, 1988; Uncles et al., 1995).

Consumers also increase the amount they spend in order to obtain a higher level of utilitarian reinforcement, that is, in order to obtain, occasionally, a more sophisticated formulation of the product. This is in agreement with the strong market tendency of presenting a wide range of formulations of routinely-purchased food products. The level of informational reinforcement of brands showed significant, but small effects upon the amount of spending. In the case of cookies, the parameters were negative although very close to zero. Small effects of informational reinforcement cannot be viewed as surprising in the case of grocery food products, which typically constitutes a consumer setting with low level of programmed informational reinforcement (cf. Foxall, 1990; 1998). These results, concerning

informational reinforcement level, are in line with those reported in previous investigations that have analyzed intra- and inter-brand demand elasticities, which showed smaller effects of informational reinforcement than utilitarian reinforcement and price promotions (Oliveira-Castro et al., 2005).

There were large differences in the size of R^2 across product categories. Whereas this measure was quite high for baked beans, above .75, it was much lower for cookies, around .20. Fruit juice and yellow fats showed intermediate values. Although it is not possible, with the available information to identify the sources of such discrepancies, some differences across products may be related to this finding. The number of purchases made by each consumer is one of the factors that differed greatly among the four products. This can be seen by the total number of data points generated during the same period of time, which was the largest for cookies, the product with the lowest value of R^2 , and the smallest for baked beans, which showed the largest value of R^2 . These larger number of purchases made during 52 weeks can be related to two differences in buying pattern: it could be due to shorter inter-purchase intervals and/or larger number of purchases on each shopping trip. An examination of the reduction of data points when using weekly data suggests that products with larger number of purchases showed both shorter inter-purchase intervals and larger number of purchases on each shopping trip. If products had different number of purchases on each shopping trip but similar inter-purchase intervals, they would show similar number of data points in the weekly data. If they had similar number of purchases on each shopping trip but different inter-purchase intervals, the proportion of data points should remain the same, across products, when switching from the all-data analysis to the weekly analysis. As both the proportion of data points number and the number of data points in the weekly analysis differ greatly across the four products, one can conclude that products differ with respect to both

variable, that is, consumers buy cookies more frequently than baked beans and they also buy a larger number of brands on each shopping occasion.

Such differences in buying patterns may be indicative of differences in homogeneity across markets. Larger purchase frequencies, particularly on the same shopping occasion, may be related to purchases of items that belong to different subcategories of products and do not function as substitutes. In the case of cookies, for example, on the same shopping trip, consumers may purchase sweet cookies for the children, sweet cookies for afternoon tea, cookies to be included in dessert recipes, and savory biscuits to accompany alcoholic beverages. These items, although typically classified as *cookies* (biscuits in the UK), may not be functional substitutes. In contrast, a product category such as baked beans does not include such variety of item; it is a much more homogeneous product category. Now, if this analysis is correct, choices among items in the cookies category are not choices among brands of the same type of product, whereas choices among items in the baked beans category are much more like choices among brands of the same product. As the proposed model is a model of choice of brand attributes, it would not be surprising if it shows better adjustment to more homogeneous product categories such as baked beans. This interpretation is corroborated by the higher values of R^2 observed for weekly data. In the case of weekly data, although consumers may be purchasing items belonging to different subcategories of the product on each shopping occasion, such differences would be diminished by the averaging procedure, for consumers probably buy a similar bundle of subcategory items on every week they make their grocery shopping.

The present findings corroborate the usefulness of the BPM as a framework to interpret consumer behavior. The combination of behavioral economics tools, such as the matching law, with the concepts proposed by the model seems to open a promising avenue for the investigation of consumer behavior.

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Table 1. Equation 4 parameters calculated for each product category using data from all purchases of all consumers and weekly-averaged data.

All purchases on all shopping trips				Weekly averaged purchases		
Baked Beans $R^2 = .755$ $n = 13,713$				$R^2 = .775$ $n = 11,666$		
	Value	Error	p	Value	Error	p
$Log_n k$	0.04	.002	<.000	0.03	.002	<.000
s_1	0.85	.004	<.000	0.86	.005	<.000
s_2	0.78	.010	<.000	0.66	.011	<.000
s_3	0.26	.004	<.000	0.24	.004	<.000
s_4	-0.85	.015	<.000	-0.86	.015	<.000
Cookies $R^2 = .207$ $n = 74,324$				$R^2 = .227$ $n = 32,452$		
	Value	Error	p	Value	Error	p
$Log_n k$	-0.07	.002	<.000	-0.05	.002	<.000
s_1	0.38	.003	<.000	0.43	.005	<.000
s_2	0.23	.006	<.000	0.20	.009	<.000
s_3	-0.01	.003	.001	-0.01	.004	<.000
s_4	-0.68	.011	<.000	-0.64	.021	<.000
Fruit Juice $R^2 = .310$ $n = 21,247$				$R^2 = .336$ $n = 15,032$		
	Value	Error	p	Value	Error	p
$Log_n k$	-0.04	.003	<.000	-0.03	.003	<.000
s_1	0.45	.005	<.000	0.50	.006	<.000
s_2	0.21	.015	<.000	0.25	.019	<.000
s_3	0.12	.007	<.000	0.13	.008	<.000
s_4	-0.90	.027	<.000	-0.86	.032	<.000
Yellow Fats $R^2 = .442$ $n = 30,538$				$R^2 = .485$ $n = 24,845$		
	Value	Error	p	Value	Error	p
k	-0.01	.002	<.000	-0.01	.002	.015
s_1	0.68	.005	<.000	0.71	.005	<.000
s_2	0.34	.010	<.000	0.33	.011	<.000
s_3	0.13	.005	<.000	0.14	.005	<.000
s_4	-0.94	.013	<.000	-0.92	.014	<.000