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POSTREINFORCEMENT PAUSE IN GROCERY SHOPPING: COMPARING INTERPURCHASE TIMES ACROSS PRODUCTS AND CONSUMERS

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Purchase probability as a function of interpurchase time was examined through comparison of findings from laboratory experiments on reinforcement schedules and from marketing investigations of consumers' interpurchase time. Panel data, based on a sample of 80 consumers who purchased nine supermarket food products during 16 weeks, were used. For each product category, interpurchase time was similar for each shopping occasion and cumulative purchase probability increased as a Gamma function of the time since the last purchase. A comparison of interpurchase times across products and consumers showed that average interpurchase time differed across four subsets of products and across seven groups of consumers, with a significant interaction effect. Interpurchase times tended to be longer after larger purchases, as would be predicted from laboratory results. A correlation between individual interpurchase time and number of products bought on each shopping occasion indicated that consumers who shop more frequently buy larger numbers of products per occasion. These results have several managerial implications and demonstrate the usefulness of a behavior-analytic framework in the interpretation of consumer behavior.

The concept of reinforcement is central to operant theory. When interpreted as an operation rather than a process, it has been usually defined as *the delivery of a reinforcer when a response occurs* (Catania, 1998; Skinner, 1953). A reinforcer, in turn, is commonly defined as *any event that when produced by a response increases its likelihood under similar conditions*. So, by definition, reinforcement of a response increases the probability of the response occurring under similar circumstances. When events that function as reinforcers for certain organisms under certain conditions are identified, for example, food for

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a deprived rat, empirical and practical investigations can be conducted. The study of reinforcement schedules is a good example of empirical research ensuing from such conceptualizations and represents one of the novelties in Skinner's proposal (Staddon & Cerutti, 2003). Reinforcement schedules are arrangements of reinforcement based on certain rules, such as time intervals (e.g., for each response after each period of 30 s since the previous reinforcement) or response requirements (e.g., for each 10th response), which can be varied and combined to form a wide range of complex schedules (Ferster & Skinner, 1957). Experimental investigations usually involve responses that can be easily repeated and are emitted many times during experimental sessions, such as pressing a lever for rats or pecking a disk for pigeons (Staddon & Cerutti). The experimental study of behavior under reinforcement schedules has led to a large and impressive body of research that has revealed many and unsuspected systematic effects of such arrangements.

One such discovery is the finding that reinforcement usually produces a postreinforcement pause, that is, the probability of response is usually very low immediately after, for example, each delivery of food in experimental schedules with animals. In reinforcement schedules based on time rules, such as a fixed-interval schedule, in which the probability of reinforcement immediately after reinforcement is zero, this pause has been interpreted as wait time and as being part of interval timing patterns. In fixed-interval schedules, for example, two different patterns have been more frequently observed (cf. Catania, 1998; Ferster & Skinner, 1957). One of them is a scalloping pattern, with a well-defined postreinforcement pause followed by a positively accelerating rate of responses until the end of the interval and delivery of the next reinforcer. The other pattern is a constant-responding pattern, in which responding resumes after the postreinforcement pause and occurs with a constant rate until the end of the interval. Considering that the pause may also be influenced by other factors, such as degree of food deprivation, which may decrease after reinforcement, special procedures have been developed to investigate interval timing more accurately (Staddon & Cerutti, 2003). That postreinforcement pauses are also observed in ratio schedules, where reinforcement is dependent on the emission of a given fixed or variable number of responses, suggests that factors other than timing are involved in the production of postreinforcement pauses. The observation of pauses, directly proportional to reinforcement magnitude, under constant-probability schedules has led some authors to conclude that postreinforcement pauses are, at least in part, due to an unconditioned suppressive property of reinforcement (Harzem, Lowe, & Priddle-Higson, 1978).

Findings derived from experimental investigations of reinforcement schedules have been frequently used to interpret complex behavioral phenomena occurring outside the laboratory. Piecework payment in industry, for example, has been compared with ratio schedules (Skinner, 1953), whereas brand choice in grocery shopping has been interpreted as concurrent ratio schedules (Foxall, 1999). In the present article, some of the findings concerning postreinforcement pause and interreinforcement response patterns are related to patterns of grocery shopping. The purchase of supermarket products, usually called in marketing *fast-moving consumer goods*, is frequent and repeated and, in this sense, resembles schedules in which the response occurs repeatedly according to some rule. According to this analogy, each time a person buys a given product would be similar to one trial followed by reinforcement under laboratory schedules.

Some differences are also clear in such an analogy. In grocery shopping, the deprivation level after each purchase is substantially changed, for the person usually buys a quantity that is sufficient to last for a week or more. By contrast, in most experimental investigations where food or water are used as reinforcers, very small amounts of food or water are delivered on each trial with the purpose of keeping the deprivation level constant across the entire session. Exceptions to this type of procedure can be found in experiments that adopt closed-economic settings (e.g., Hursh, 1984) or long-duration sessions (Todorov, Hanna, & Bittencourt de Sá, 1984). Most natural situations seem to be similar in this respect to grocery shopping where each reinforcement substantially reduces deprivation levels; examples include getting a glass of water, reaching for a screwdriver, and eating a meal. A distinction between what could be termed the *contingency cycle*, that is, the time between reinforcements, and the *establishing operation (or deprivation) cycle*, that is, the time (or number of reinforcements) necessary to change the reinforcing value of an event, such as the presentation of food, may help stress the differences between typical laboratory procedures and most natural situations. In the case of the former, contingency and establishing-operation cycles are different, whereas in the latter, they are the same (e.g., a meal can function as a reinforcer for going into a restaurant and may be sufficient to decrease, temporarily, the reinforcing value of food). After considering the type of schedule involved in grocery shopping, Foxall (1999) proposed that it is more similar to ratio schedules than interval schedules, for there is no time requirement for purchasing and the purchase of a product requires the expenditure of a discrete number of monetary units.

In the marketing literature, interpurchase time has been conceived by some authors as one of the main components of consumers' purchase decisions, since a consumer must decide what, when, and how much to buy (e.g., Gupta, 1988). Estimating when consumers will purchase within a given product category is essential to the success of several managerial activities, such as stock replacement, number of open cashiers, size of the store, among other things. During the past 30 years, many researchers have attempted to model the changes in probability of purchasing a product during interpurchase times (cf. Seetharaman & Chintagunta, 2003). Although the mathematical details of such models are not central to the present article, some interesting empirical results stem from this type of research. One of them is that most statistical distributions (depending, of course, on certain parameters) used to describe the changes in probability of purchasing a product as the time since the last purchase increases (e.g., Gamma, Erlang 2, or exponential) predict that this cumulative probability tends to be positively accelerated at the beginning of the interval and negatively accelerated when the end of the interval approaches (cf. Seetharaman, 2004). This is particularly interesting when such results are compared with those found in the study of reinforcement schedules in the laboratory, where different patterns are usually observed. Another interesting finding is that consumers tend to make their shopping trips in discrete intervals, usually weekly (cf. Chiang, Chung, & Cremers, 2001; Kahn & Schmittlein, 1989). Moreover, a large body of research indicates that interpurchase time, as measured with purchase frequency, changes only slightly across brands within a given product category, despite large differences in their levels of penetration (Ehrenberg, 1988/1972; Uncles, Ehrenberg, & Hammond, 1995). Taken together, these results suggest that, for routinely purchased consumer goods, interpurchase time is a relatively constant characteristic of buying patterns and that purchase probability tends to be positively accelerated at the beginning of the interval and negatively accelerated closer to its end.

The analysis of responding under reinforcement schedules in the laboratory suggests that interpurchase time would be formed by a postpurchase pause followed by either an increase in purchase probability as time since the last purchase elapses or a constant purchase probability from the pause until the end of the interval. Contrary to this prediction, the results from research of interpurchase time suggest that purchase probability would increase after the postpurchase pause and decrease closer to the end of the interval.

The examination of these two predictions is the main purpose of the present article, that is, to analyze the change in purchase probability as time since the previous purchase increases, analogously to analyses of responding in reinforcement schedules. The results can then be compared with those reported in research on interpurchase time. The data used here were obtained from a consumer panel, a set of consumers that record information concerning their grocery purchases of some products. Such panels are usually maintained by commercial firms who sell the information to retailers, producers, and researchers. Consumer panels usually contain information about large numbers of consumers buying different products. Considering that, in the case of grocery shopping, contingency and establishing-operation cycles coincide (i.e., each purchase functions as reinforcement and diminishes reinforcing value), interreinforcement periods include only one instance of responding (i.e., purchasing) per consumer. This cycle coincidence implies that the response probability during each interreinforcement period simply changes from zero to one for each consumer. This all-or-none change in probability, from zero to one, may occur even across several interreinforcement periods for the same consumer, if purchase occurs with the same periodicity (e.g., once a week). This characteristic of grocery shopping suggests that calculating purchase probability for individual consumers may be less fruitful than calculating it for groups of consumers or across consumers, which was done in the present article. Changes in purchase probability, calculated for groups of consumers and across consumers, as a function of time since previous purchase were examined.

As the literature on reinforcement schedules indicates that reinforcement may have an unconditioned suppressive effect, which has been identified from increases in postreinforcement pause duration as a function of increases in the magnitude of the preceding reinforcement (Harzem et al., 1978), we also examined whether interpurchase durations were related to changes in quantity of a given product bought during the preceding shopping occasion. Marketing results show that promotions may generate increases in stockpiling and interpurchase times (e.g., Gupta, 1988), although the functional mechanisms associated with each of these phenomena are probably distinct.

Considering, moreover, that consumer behavior can be interpreted as the result of interactions between consumer settings and individual histories (cf. Foxall, 1990, 1998), it was decided also to investigate the relative importance of individual differences and product differences on consumer buying patterns. This inquiry involved looking at the changes in interpurchase time as a function of previously measured mean product and mean consumer interpurchase times.

Searching for other regularities in buying patterns related to interpurchase duration, we also examined whether consumers who go shopping less frequently tend to buy a larger number of products on each shopping occasion. This investigation was performed by calculating the correlation between mean consumer interpurchase time and mean number of products bought on each shopping occasion.

Method

Participants

Consumer panel data for 80 consumers randomly selected from the TNS (Taylor Nelson Sofres, a market-research company) "Superpanel" were used. This panel consists of 15,000 British households and provides data on a range of consumer goods. The 80-consumer sample was representative of the UK population as a whole in terms of demographics, age, and so forth. As the analysis of interpurchase time requires information concerning actual purchase across several buying opportunities, data from consumers who bought, within each product category, fewer than four times during the selected period were disregarded.

Material

Data included consumers' total weekly purchases, during a period of 16 weeks, of each of nine product categories: baked beans, biscuits (cookies), breakfast cereals, butter, cheese, fruit juice, instant coffee, margarine, and tea. The following information was recorded for each purchase of each consumer: brand specification (i.e., different versions of the same product category were classified as different brands, e.g., Corn Flakes and Rice Krispies by Kellogg's), package size, shop, date (on a weekly base), number of units, and total amount spent.

Procedure

Voluntary participant members of this consumer panel scan their purchases into a sophisticated handheld barcode reader after each shopping trip by simply passing the scanner across the product codes on the packages. The data are then sent electronically to Taylor Nelson Sofres for central processing. Panel data were chosen, as they are especially advantageous for longitudinal studies: changes in behavior, in this case purchasing behavior, can be well monitored by means of the continuous measurements (Crouch & Housden, 2003). Moreover, diary panel data are also believed to be very accurate and freer from errors intrinsic to reporting of past behavior (Churchill, 1999); therefore they are particularly valuable in the collection of information on variables such as price, shopping occasion, and brand name. The noteworthy reliability of the study is that the data were obtained in a nonexperimental, computer-assisted way by monitoring real-world consumers as they spent their real disposable income on fast-moving consumer goods.

This article presents a descriptive analysis of the naturally occurring behavior of a large group of people and compares it to models of individual behavior investigated in the laboratory. This analogy resembles recent investigations of complex phenomena that occur in natural settings, such as playing-calling in football (Reed, Critchfield, & Martens, 2006) and scalloping patterns in congressional bill approval (Critchfield, Haley, Sabo, Colbert, & Macropoulis, 2003).

Results

Table 1 presents information concerning the number of consumers, the number of purchases, the average number of purchases, and the total amount spent per consumer for each product category. As can be seen in the table, most of these measures varied considerably across product categories. The number of consumers with four or more purchases during the 16-week period within each product category, for example, ranged from 19 for coffee to 59 for biscuits, whereas the total number of purchases ranged from 144 to 1,125, also for coffee and biscuits, respectively. These wide differences across categories suggest that different products were associated with different purchase frequencies and, consequently, with different interpurchase durations. In the case of the present data set, all interpurchase durations were measured in numbers of weeks.

Considering that only consumers with four or more purchases in each product category during the 16-week period were included in the data set, a minimum of three entire interpurchase periods for each consumer were available for analysis. Figure 1 shows purchase probability, calculated across all consumers who bought items in each product category, as a

Table 1

Consumers, Purchases, and Amount Spent (in British pounds)

Product	No. of Consumers	Total No. of Purchases	Average No. of Purchases	Total Spent per Consumer
Baked beans	39	265	6.79	4.52
Biscuits	59	1,125	19.07	14.02
Breakfast cereals	56	691	12.34	20.09
Butter	21	174	8.29	9.84
Cheese	45	447	9.93	13.38
Fruit juice	34	336	9.88	13.99
Coffee	19	144	7.58	18.32
Margarine	50	401	8.02	8.75
Tea	32	199	6.22	11.67

function of week number (in the 16-week period), for each of the three interpurchase intervals (i.e., between shopping occasions). Purchase probabilities were obtained by dividing the cumulative sum of the number of consumers who bought the product on any given week by the total

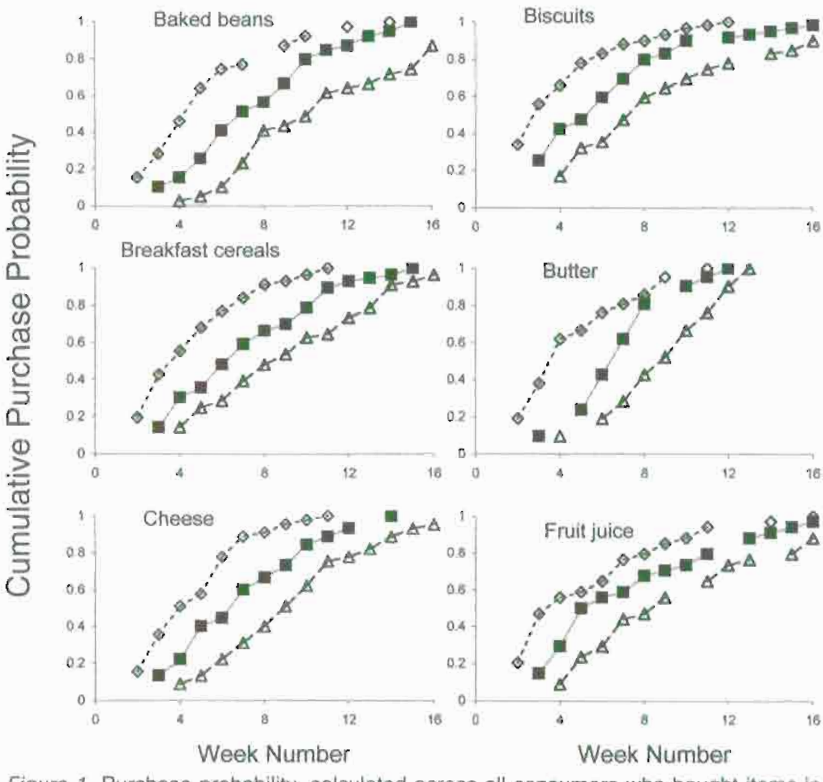

Figure 1. Purchase probability, calculated across all consumers who bought items in each product category, as a function of week number, for each of the three interpurchase intervals. Diamonds, squares, and triangles denote Shopping Occasions 1, 2, and 3, respectively.

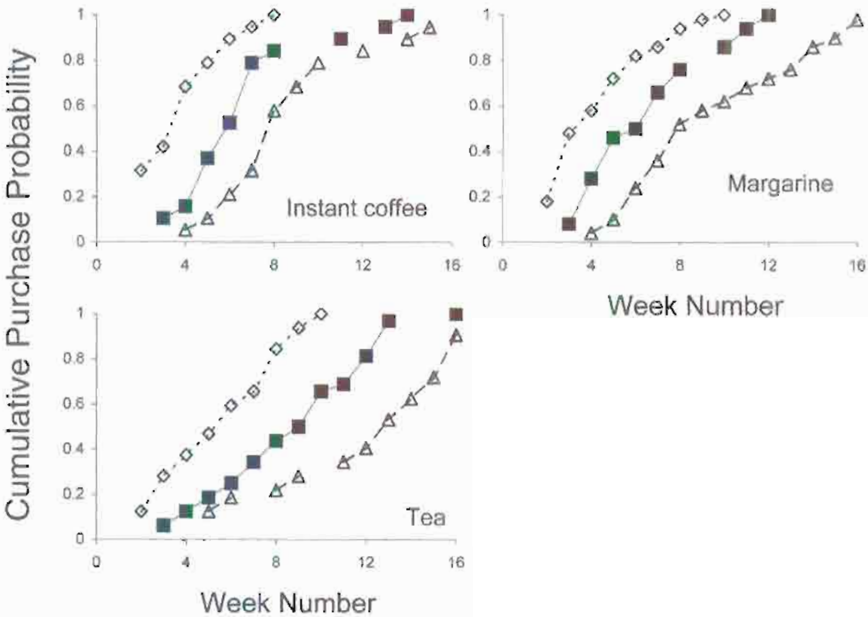

Figure 1. continued

number of consumers who bought the product four or more times (e.g., total number was equal to 39 for baked beans; see Table 1). These probabilities were calculated for each product category by using the second shopping occasion of all consumers, then the third shopping occasion of all of them, and then the fourth occasion (since all bought at least four times). As can be seen in Figure 1, increases in purchase probability as a function of week number were, in general, negatively accelerated and were similar across shopping occasions and products (more detailed analyses are presented below).

For each product, the function for each shopping occasion can be visually distinguished from the others, suggesting that shopping occasions differed with respect to their mean week number. To test such differences, analyses of variance (involving Tukey post hoc tests) were conducted to compare the mean week numbers of shopping occasions for each product category. These results are shown in Table 2, which presents the mean week number for each shopping occasion and the statistics associated with their comparisons (*F* ratios, significance levels, and number of data points). As can be seen in the table, mean week numbers differed significantly ($p \leq .05$) across all three shopping occasions for seven of the nine product categories. For the other two products, only two of the mean week numbers were statistically different (for fruit juice, week number for Shopping Occasion 2 did not differ from the other two, whereas for instant coffee, week number for Shopping Occasion 2 did not differ from that for Shopping Occasion 3). These results indicate that statistically, three

Table 2

Mean Number of Weeks as a Function of Shopping Occasions

Product	Shopping Occasion	*N*	Mean No. of Weeks	*F*-ratio	*p*	Post Hoc Tests
Baked	1	39	5.51			1 < 2 (.005)
beans	2	39	7.95	17.15	<.000	2 < 3 (.019)
	3	34	10.12			1 < 3 (<.000)
Biscuits	1	59	4.17			1 < 2 (.002)
	2	58	6.21	19.83	<.000	2 < 3 (.013)
	3	53	7.94			1 < 3 (<.000)
	1	56	4.73			1 < 2 (<.000)
Breakfast	2	56	7.25	24.10	<.000	2 < 3 (.013)
cereals	3	54	9.04			1 < 3 (<.000)
Butter	1	21	4.81			1 < 2 (.018)
	2	21	7.05	17.19	<.000	2 < 3 (.038)
	3	21	9.05			1 < 3 (<.000)
Cheese	1	45	4.89			1 < 2 (.001)
	2	45	7.20	23.69	<.000	2 < 3 (.005)
	3	43	9.23			1 < 3 (<.000)
Fruit juice	1	34	5.47			1 ≈ 2 (.158)
	2	33	7.21	6.01	.003	2 ≈3 (.235)
	3	30	8.80			1 < 3 (.002)
Coffee	1	19	3.95			1 < 2 (.004)
	2	19	6.79	14.68	<.000	2 ≈ 3 (.110)
	3	18	8.56			1 < 3 (<.000)
Margarine	1	50	4.44			1 < 2 (< .000)
	2	50	6.70	36.93	<.000	2 < 3 (< .000)
	3	49	9.49			1 < 3 (<.000)
Tea	1	32	5.72			1 < 2 (< .000)
	2	32	9.03	24.43	<.000	2 < 3 (.007)
	3	29	11.69			1 < 3 (<.000)

Note. Numbers of data points (*N*), mean week numbers, *F*-ratios, significance levels (*p*), and results of post hoc tests (including *p*) are shown for each product category.

(or two) different interpurchase intervals were identified for each product category, allowing for more detailed analyses of the increase of purchase probabilities during such intervals.

The apparent similarity (across occasions and products) in the shape of the curves that related purchase probability, calculated across consumers, to week number (Figure 1) suggests the possibility of identifying an equation to describe changes in cumulative purchase probability as a function of interpurchase time. Examining the goodness of fit of different equations might also shed some light on the general shape of the curve, considering that laboratory investigations of reinforcement schedules would suggest positively accelerated increases in purchase probability, whereas marketing studies of interpurchase time have reported negatively accelerated increases in probability close to the end of the interval. The fit of five types of functions were tested, namely, linear, logarithmic, power, exponential, and cumulative-Gamma (as

Erlang 2 and cumulative exponential are special cases of this, they were not included), using all data points from all products and all data points for each product. These functions were chosen because of their simplicity and their frequent use in related research. The linear function may be used to test for the second pattern found in fixed intervals (pause followed by constant rate), whereas the others have been frequently used in research on consumption patterns (e.g., DiClemente & Hantula, 2003; Oliveira-Castro, Ferreira, Foxall, & Schrezenmaier, 2005; Seetharaman, 2004). The analyses considered cumulative purchase probability as a function of time since previous purchase. Probability was calculated for each consumer by dividing the cumulative number of purchases at a given interpurchase time by the total number of purchases made by that same consumer (the last probability for each consumer being therefore equal to 1). Figure 2 illustrates the type of data used for fitting the functions. In the figure, data from ten randomly selected consumers who purchased cheese are shown. Each line represents the cumulative purchase

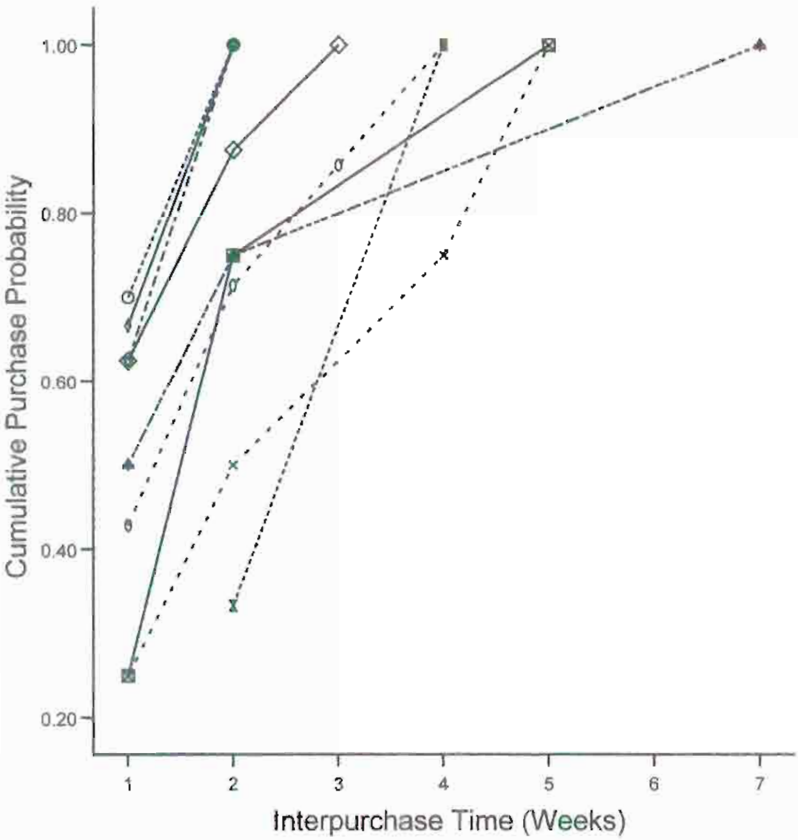

Figure 2. Cumulative purchase probability as a function of interpurchase time for each consumer. Data from ten randomly selected consumers who purchased cheese are shown, where each marker (and line) represents data for a different consumer.

probability as a function of interpurchase time for each consumer. As can be seen, purchase probability tended to increase with increases in interpurchase time, suggesting a negatively accelerated curve for longer values of interpurchase time. Curve fitting included these types of data points from all consumers purchasing all products, for overall fitting, and from all consumers purchasing each product, for product-specific fitting.

Table 3 shows determination coefficients, numbers of cases, and values of the two parameters (b_0 and b_1; for the Gamma, shape and scale) obtained for each of the five functions, using data from all products and from each of them. All analyses for the five functions yielded significant results ($p < .05$). Determination coefficients obtained for the five functions were in general similar and ranged from .190 (exponential for fruit juice) to .626 (Gamma for coffee). Despite such similarities, the cumulative-Gamma function showed higher determination coefficients than the other four for the overall analysis and for seven of the nine products (the exceptions being the logarithmic function for butter and tea). The logarithmic function presented the second best fit, showing determination coefficients higher than the other three functions for the overall analysis, including all products, and for all the nine product-specific analyses. Taken together, these results suggest that the cumulative-Gamma (and the logarithmic) equation describes increases in cumulative purchase probability as a function of interpurchase time reasonably well, which implies that probability increases are somewhat negatively accelerated by the end of the interval.

To investigate possible suppressive effects of reinforcement, a correlation coefficient (Pearson) that related interpurchase durations to changes in the quantity bought on preceding occasions was calculated. This calculation involved all data points available in the sample, that is, all data points from all consumers who bought all nine products. Because the quantity bought in each product category differed markedly (quantity scales also differed), relative measures of interpurchase duration and of quantity were adopted by means of dividing both measures by the average of interpurchase durations and quantities bought that were observed for each product category. The results indicated that increases in the quantity of a given product bought by consumers on the preceding occasion were associated with significant increases in the duration of interpurchase intervals ($r = .044$, $N = 2182$, $p = .019$).

To examine the relative influence of individual differences and situational factors on shopping frequency, a multiple linear regression analysis was conducted where interpurchase duration was a function of mean interpurchase durations calculated for each consumer (across products) and calculated for each product (across consumers). Mean interpurchase durations for each consumer and for each product were obtained with data from the first interpurchase interval. These values were then used to predict the values of interpurchase durations observed on the remaining two intervals (second and third). The multiple regression indicated a significant relation between interpurchase durations and the predictors ($R^2 = .03$, *F ratio* $= 9.25$, $p < .000$), in general, and that both

Table 3

Cumulative Purchase Probability in Relation to Interpurchase Time

Product	Function	R^2	N	b_0 (or shape)	b_1 (or scale)
All	Linear	.365	993	.498	.089
	Logarithmic	.442		.519	.274
	Power	.391		.473	.450
	Exponential	.304		.463	.142
	Cum. Gamma	.448		.807	.512
Baked beans	Linear	.485	113	.416	.107
	Logarithmic	.568		.446	.320
	Power	.510		.415	.536
	Exponential	.409		.400	.174
	Cum. Gamma	.571		1.040	.598
Biscuits	Linear	.333	154	.542	.094
	Logarithmic	.386		.589	.255
	Power	.338		.529	.421
	Exponential	.273		.496	.149
	Cum. Gamma	.387		.717	.554
Breakfast Cereal	Linear	.317	156	.527	.081
	Logarithmic	.427		.529	.275
	Power	.371		.477	.458
	Exponential	.259		.480	.132
	Cum. Gamma	.447		.935	.633
Butter	Linear	.465	63	.540	.087
	Logarithmic	.516		.568	.252
	Power	.402		.552	.353
	Exponential	.357		.532	.121
	Cum. Gamma	.507		.633	.434
Cheese	Linear	.449	126	.455	.107
	Logarithmic	.544		.492	.310
	Power	.484		.455	.504
	Exponential	.379		.434	.169
	Cum. Gamma	.562		1.156	.770
Fruit juice	Linear	.223	86	.582	.063
	Logarithmic	.280		.582	.213
	Power	.253		.527	.348
	Exponential	.190		.531	.100
	Cum. Gamma	.284		.516	.327
Coffee	Linear	.510	61	.472	.094
	Logarithmic	.614		.493	.289
	Power	.538		.457	.475
	Exponential	.413		.450	.149
	Cum. Gamma	.626		.918	.566
Margarine	Linear	.440	147	.437	.108
	Logarithmic	.519		.475	.312
	Power	.462		.437	.519
	Exponential	.372		.415	.176
	Cum. Gamma	.526		1.022	.629
Tea	Linear	.371	87	.432	.084
	Logarithmic	.397		.431	.274
	Power	.382		.402	.464
	Exponential	.334		.409	.137
	Cum. Gamma	.393		.690	.301

Note. Determination coefficients, numbers of data points (N), and parameters (b_0 and b_1; for the Gamma, shape and scale) associated with the functions linear, logarithmic, power, exponential and cumulative-Gamma, relating cumulative purchase probability to interpurchase time, calculated with data points from all products and from each product.

mean interpurchase duration obtained for consumers ($p = .046$) and for product ($p < .000$) were significantly related to interpurchase durations obtained at a later time. Moreover, the regression results indicated that products ($b_1 = .60$) had a stronger effect, as measured with regression parameters, than individual consumer patterns ($b_2 = .14$).

Considering that shopping frequency may be related to the number of products consumers buy on each shopping trip (higher frequency related to fewer products?), a correlation coefficient (Pearson) that related mean consumer interpurchase durations and number of products purchased on each shopping trip was calculated with all data points from all consumers who purchased all products. The results indicated that increases in consumer average interpurchase intervals (i.e., decreases in shopping frequency) were associated with decreases in the number of products purchased on each shopping occasion ($r = -.54$, $N = 76$, $p < .000$).

Discussion

The present article applies concepts and adapted measures used in experimental investigations of responding under reinforcement schedules to the analysis of patterns of buying some grocery products. In general, the results suggest that such application is useful in the task of interpreting and characterizing behavioral patterns of consumers and can complement more typical marketing analyses of such phenomena.

The finding that successive interpurchase intervals were clearly distinguishable for almost all the products investigated (Table 2) suggests that purchasing of a given grocery product can be analyzed in purchasing cycles, which begin when the first consumer makes her purchase of the product and ends when the last one does so. This is not a trivial finding, for such shopping cycles could very well be indistinguishable. If consumers differed widely with respect to their interpurchase interval for a given product, most consumers could be repeating their purchases of the product (i.e., initiating their following purchase cycle) before others bought it for the first time in that cycle. This phenomenon occurred in the intermediary shopping interval for fruit juice and instant coffee, which did not differ significantly from the first and last interpurchase intervals examined here.

This possibility of identifying different shopping intervals across consumers strengthens the analogy with interreinforcement intervals and opens the way for a more detailed analysis of changes in purchase probability within each interval. The results show significant and systematic increases in purchase probability, calculated for each consumer, for all product categories. The level of regularity in the data even suggests the possibility of identifying a specific function to describe the phenomenon. The cumulative-Gamma showed the best fit and was followed closely by the logarithmic function. These results corroborate the extensive marketing literature on interpurchase duration, which has repeatedly reported that interpurchase times across consumers tend to occur according to a Gamma-type distribution (including Erlang; cf. Seetharaman & Chintagunta, 2003). In the present study, the fact that the logarithmic function fit the data almost as well as the cumulative-Gamma did may have been due to the measure of interpurchase time adopted. As this interval was measured in weeks, rather than in days, the shape parameter of the Gamma distributions assumed low values (close to or smaller than 1.0), indicating an abrupt increase in probability at the beginning of the interpurchase interval. Considering that consumers' grocery shopping tends to have a weekly cycle (cf. Chiang et al., 2001; Kahn & Schmittlein, 1989), the week measure may be too coarse to capture subtler transitions.

Even though this study does not aim at modeling changes in purchase probability with increases in interpurchase time, as is typically done in the marketing literature, the evidence that the cumulative-Gamma and logarithmic functions showed the best fit to the data suggests that increases in cumulative purchase probability, close to the end of the intervals, are negatively accelerated. This corroborates empirical findings about interpurchase time and questions the analogy proposed here with reinforcement schedules. In this latter case, increases in cumulative probability should have been positively accelerated. These observed differences between performance under reinforcement schedules and interpurchase times stress, once more, the need for careful extrapolations when interpreting naturally occurring phenomena in light of laboratory findings (cf. Foxall, 1998; Harzem, 1986). In the present case, as mentioned earlier, one of the possible important differences between the two sets of phenomena, which may explain in part such results, seems to be based on the fact that whereas in grocery shopping, contingency and establishing-operation cycles coincide, they usually differ in typical investigations of performance under reinforcement schedules. Investigations of instances of the former in the laboratory and instances of the latter in natural settings may help elucidate this research question.

These discrepant results also may be related to differences in the procedures adopted in typical laboratory fixed-interval schedules and grocery shopping situations. In the latter, because the quantity consumers buy can vary on each shopping occasion, consumers can stockpile and skip purchasing in the product category on the following shopping occasion (cf. Gupta, 1988). In fact, the observed increases in interpurchase interval associated with increases in the quantity bought in the preceding occasion suggest that such stockpiling occurred. This increased "postreinforcement" pause might have been due to an unconditioned inhibiting effect of reinforcement (Harzem et al., 1978), which would then be generalized to humans behaving in natural situations outside the laboratory. It may also be related to basic differences between human and animal reinforcement patterns, where the former usually include social and verbal contingencies that make possible planning or rule-following behavior (e.g., Hayes, Barnes-Holmes & Roche, 2001; cf., however, Foxall, 2004, 2005). Although interpurchase duration and quantity bought on the previous occasion were significantly correlated, the value of the correlation coefficient was quite small, which probably reflects the expected influence of several other variables. This small effect corroborates results from previous investigations that showed slight effects of marketing activities on interpurchase duration (or repeat-buying rate; e.g., Ehrenberg, Hammond, & Goodhardt, 1995; Gupta, 1988; Sharp & Sharp, 1997). One of the practical implications of this finding is the possibility of observing a small increase in interpurchase interval after, for example, a price promotion in which consumers increase the quantity they buy.

Considering that the sample was not large (for marketing purposes) and only three full shopping cycles could be examined, the present results cannot be interpreted as giving additional information to modeling attempts. Despite such limitations, the fact that the results corroborate those from much larger samples of consumers during much longer times (for example, the study by Seetharaman & Chintagunta, 2003, which used 300 households during 2 years) suggests that the present results are reliable.

These findings have clear managerial implications. Once the typical cycle duration for each product and its purchase probability function are identified, one could predict the number of different consumers who buy the product at any given time during the cycle. By combining, for example, information concerning the market share of the brand with information concerning consumers' shopping cycle duration of the product, producers and retailers could plan promotional strategies accordingly, estimating how many consumers are buying and how many are repeat-buying during the promotion.

The observation of significant effects of mean product and mean consumer interpurchase duration on later interpurchase durations gives additional support to the general proposal that consumer behavior is the result of interactions between events in the consumer setting and individual histories of consumption. The finding that suggests product characteristics may have stronger influence than individual ones also corroborates the importance of emphasizing the effects of situational variables on consumer behavior, which have been much neglected in the predominant social-cognitive interpretation (cf. Foxall, 1990, 1998).

The observed negative correlation between interpurchase interval and number of products purchased on each shopping occasion runs somewhat against intuitive expectations. It would seem more reasonable to suppose that consumers who shop less frequently also buy a larger number of products on each shopping trip. The result contradicts this prediction and may have been due to procedural characteristics. Considering that the data set contained information about only nine products and that most consumers may buy on each shopping trip many other products not included in the sample, the observed correlation may be a consequence of the subset of products selected. This observation suggests the need to investigate these relations with samples that include larger numbers of product categories, although the present findings may serve as a first step in this direction.

This line of investigation could be followed up in several directions. One of these is the use of some demographic information and a larger sample of consumers purchasing for longer periods. As more shopping cycles for each consumer are analyzed, it may be possible to identify and separate individual and group patterns of interpurchase time and to relate them to demographic characteristics, which may enrich functional analyses of the phenomena. Our research group has explored some of these possibilities using a much larger data set (Foxall, James, Chang & Oliveira-Castro, 2007). Another promising line of research is the adoption of ecologically relevant experimental procedures that would permit systematic manipulations of interpurchase time and reinforcement magnitude (e.g., DiClemente & Hantula, 2003).

Finally, our research has been concerned with an aspect of consumer behavior that is often not of central concern to behavior analysts: the temporal allocation of resources (responses) in a purely routine sequence of consumption activities in naturally occurring settings, rather than the preference reversals over time characteristic of more extreme consumer behaviors such as addictive gambling and alcohol or drug consumption (see, for instance, Ainslie, 2001; Rachlin, 2000). While there need be no conflict between these research themes—indeed, it is vital to understand their relationship and common bases of explanation (Foxall, 2007)—we believe that immediate research effort should be given to the more mundane aspects of consumer choice.

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