The Effect of Promotion on Consumption: Buying More and Consuming It Faster

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Abstract

This paper empirically demonstrates the existence of flexible consumption rates in packaged goods products, how this phenomenon can be modeled, and its importance in assessing the effectiveness of sales promotion. We specify an incidence, choice and quantity model, where category consumption varies with the level of household inventory. We use two different functions to relate consumption rates to household inventory, and estimate the models using scanner panel data from two product categories -- yogurt and ketchup. Both provide a significantly better fit than a conventional model, which assumes a constant daily usage rate. They also have strong discriminant validity -- yogurt consumption is found to be much more flexible with respect to inventory than ketchup consumption. We use a Monte Carlo simulation to decompose the long-term impact of promotion into brand switching and consumption effects, and conclude with the implications of our findings for researchers and managers.

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1. INTRODUCTION

Researchers have spent more than a decade using scanner data to investigate the effect of sales promotion. They have established that promotion results in a significant temporal and cross-sectional *shifting* of category demand (e.g., Blattberg and Wisniewski 1989; Gupta 1988). Conspicuously, however, there is very little empirical research that measures the potential for promotion to *increase* category demand (see Chiang 1995, Chandon and Laurent 1996, and Dillon and Gupta 1996 for some exceptions), although both academics and managers appear to be well aware of the potential for such an effect (cf. Blattberg and Neslin 1990, pp. 133-135).

Promotion's effect on consumption stems from its fundamental ability to increase household inventory levels. Higher inventory, in turn, can increase consumption through two mechanisms: fewer stockouts, and an increase in the consumer's usage rate of the category. The first of these is simple – fewer stockouts mean the household has more opportunities to consume the product. Existing models of purchase incidence and purchase quantity can capture this mechanism since they allow promotion-induced purchasing to increase inventory, and therefore reduce stockouts (e.g., Chintagunta 1993, Bucklin and Lattin 1991, Gupta 1988 and 1991, Guadagni and Little 1987). In fact, Neslin and Stone (1996), in a study of purchase acceleration, noted that promotion also increased consumption "due to higher inventory levels, and hence fewer stockouts under the promotion scenario." (p. 89).

The second mechanism, which says that households increase their usage rate when they have high inventory, is supported by both economic and behavioral theory. Assuncao and Meyer (1993) show that consumption should increase with inventory, not only due to the stock pressure from inventory holding costs, but also because higher inventories allow consumers greater flexibility in consuming product without having to worry about replacing it at high prices. Scarcity theory suggests that consumers curb consumption of products when supply is limited because they perceive smaller quantities as being more valuable (e.g., Folkes, Martin and Gupta 1993). Wansink and Deshpandé (1994) show that increased inventory generated by promotion can result in a faster usage rate if product usage related thoughts are salient, i.e, for products that are perishable, more versatile in terms of potential usage occasions (e.g. snack foods), need refrigeration, or occupy a prominent place in the pantry.

Although these studies provide important theoretical justification for the existence of a flexible usage rate, we are not aware of any attempts to model this phenomenon in scanner data-based models.[1] Most purchase incidence and quantity models assume a constant usage rate for the household (e.g., Gupta 1988 and 1991; Bucklin and Lattin 1991; Chintagunta 1993; Tellis and Zufryden 1995). This omits the usage rate mechanism, potentially resulting in an under-estimate of the effect of promotion on consumption.

Our goal in this paper is to (i) demonstrate empirically the existence of the flexible usage rate phenomenon; (ii) show how it can be modeled; and (iii) illustrate its importance in evaluating the effectiveness of promotion. A function that allows usage rate to vary with the level of household inventory is embedded within a model of purchase incidence and quantity. We use two different usage rate functions to suggest alternative modeling approaches as well as to provide convergent validity for the flexible usage rate phenomenon. We estimate the complete model using each function for two product categories, yogurt and ketchup, across which the flexibility of usage rate is expected to differ substantially. Our results establish the existence of the phenomenon, and provide convergent as well as discriminant validity for the functions used to model it.

The paper is organized as follows. Section 2 describes our model, focusing on the flexible usage rate. The data used for the empirical analysis and the results of our estimation are summarized in Section 3. Section 3 also summarizes the findings of a Monte Carlo simulation

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[1] Winer (1980a and 1980b) examines the impact of advertising on consumption using panel data from a split cable experiment. However, he assumes that households consume all their inventory of the category before their next purchase.

designed to measure the increase in consumption due to promotion. Section 4 concludes the paper with a discussion of our key findings, their implications, and some suggestions for future research.

2. THE MODEL

We model the purchase incidence, brand choice, and purchase quantity decisions for a household, given a shopping trip. Household inventory is an explanatory variable in the incidence and quantity decisions, and is directly associated with the flexible usage rate phenomenon that is the central focus of our paper. We therefore begin our model description with the inventory identity and the usage rate function.

2.1 Inventory Identity

Like other researchers, we use the following identity to calculate household inventory recursively at the beginning of each shopping trip (e.g., Gupta 1988, Bucklin and Lattin 1991, Chintagunta 1993, Tellis and Zufryden 1995):

$$Inv_t^h \equiv Inv_{t-1}^h + PurQty_{t-1}^h - Consumpt_{t-1}^h \tag{1}$$

where:

Inv^h_t	=	Inventory carried by household *h* at beginning of shopping trip *t*.
$PurQty^h_{t-1}$	=	Quantity (ounces) purchased by household *h* during trip *t*-1.
$Consumpt^h_{t-1}$	=	Consumption (ounces) by household *h* since trip *t*-1.

Typically, the starting inventory for each household is set equal to the average weekly consumption level of the household.[2] Thus, the starting inventory is 7 times $\overline{C}^h$, where $\overline{C}^h$ is the household's average daily consumption level computed from an initialization period, as the total volume of product purchased by household *h* over the duration of the initialization period, divided by the number of days in the period. Then, inventory at the beginning of each *subsequent* shopping trip is calculated recursively by adding the amount purchased on the previous trip and subtracting the amount consumed *since* the previous trip.

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[2] Our empirical results in this paper are not sensitive to the particular starting inventory used.

2.2 Usage Rate Function

So far, researchers have assumed a constant daily usage rate, also equal to $\overline{C}^h$. In these models, termed the "status quo" hereafter, daily consumption is calculated as:

$$Consumpt_t^h = \min\left\{Inv_t^h, \overline{C}^h\right\} \tag{2}$$

where:

$Consumpt^h_t$	=	Consumption during day t by household h
Inv^h_t	=	Inventory held by household h at beginning of day t

Households are assumed to consume $\overline{C}^h$ ounces of the product per day if their available inventory is equal to or more than $\overline{C}^h$. If available inventory is less than $\overline{C}^h$ the entire amount is consumed (e.g., Gupta 1988).[3]

Instead of this status quo, we allow the usage rate during a given day to vary depending upon the inventory available to the household at the beginning of that day. Then, we recursively calculate inventory at the end of each day in the same way as other researchers do. Note beginning inventory on any given day is logically and temporally *prior* to the consumption during that day. We use two different functional forms for the usage rate to illustrate alternative approaches for modeling the phenomenon and to provide a test of convergent validity. These functions are described below.

2.2.1 Flexible Usage Rate: A Spline Function

One of the simplest ways to think about flexible consumption is that households may consume their inventory at a higher rate soon after a purchase (i.e., when inventory is high) compared to later times, instead of at a single constant rate .[4] This can be represented by a spline function with a single node. In order to retain heterogeneity in usage rates across households, while limiting the number of additional parameters to be estimated, we specify the spline

[3] Some researchers (e.g., Chintagunta 1993) allow inventory levels to become negative. The fit of our continuous usage rate model, described later in the paper, is significantly better than this model as well as the model in equation (2).

[4] We thank an anonymous reviewer for suggesting this approach to us.

function so that the daily usage rate is a times $\overline{C}^h$ for a period immediately after a purchase, and $\overline{C}^h$ thereafter. Further, since households may differ in their purchase frequency, we assume that the change in usage rate , i.e., the node of the spline function, occurs at one half of the household's average interpurchase time, $\overline{T}^h$. Finally, we impose the restriction that consumption on any given day cannot exceed the inventory available at the beginning of that day. Thus, the spline function is as follows:

$$Consumpt_t^h = \begin{Bmatrix} \min(Inv_t^h, a\overline{C}^h) \ \text{if } days \leq \dfrac{\overline{T}^h}{2} \\ \min(Inv_t^h, \overline{C}^h) \ \text{if } days > \dfrac{\overline{T}^h}{2} \end{Bmatrix} \tag{3}$$

where:

a	=	Parameter to be estimated
days	=	Number of days since the last purchase

This function provides a parsimonious and simple way to document the phenomenon of a flexible usage rate. If usage rate does increase with inventory, we would expect a to be greater than 1, which is the value assumed in status quo models.

2.2.2 Flexible Usage Rate: A Continuous Non-linear Function

Although simple, the spline function is not particularly appealing from a behavioral viewpoint. While it certainly makes sense for households to consume more immediately after a purchase, when inventory tends to be higher, it is difficult to see why they would consume at one constant rate for a while, and then, at some arbitrary point, switch over to a slower, but again, constant rate, irrespective of how much they purchased. The switch-over point that provides the best statistical fit could be estimated from the data, but it would add another parameter while not improving the behavioral interpretation of the function. Instead of the spline model, it is behaviorally more reasonable to assume that household consumption varies continuously and nonlinearly with actual inventory. This is the case with behavioral response to many physical stimuli, consistent with the Weber-Fechner and Power Function Laws found in the psychophysical literature (Engel Blackwell, and Miniard 1995, pp. 475-476; Stevens 1985, pp. 1-19). . We therefore specify an alternative usage rate function which models daily consumption as a continuous, non-linear function of available inventory:

$$Consumpt_t^h = Inv_t^h \left(\frac{\overline{C}^h}{\overline{C}^h + (Inv_t^h)^f} \right) \qquad (4)$$

Insert Figures 1 and 2 About Here

This function, whose shape is depicted in Figures 1 and 2, has several additional desirable characteristics:

(i) It is parsimonious with only a single parameter "*f*" to be estimated;

(ii) Consumption does not exceed available inventory, so there is no need to truncate consumption as in the case of the spline function;

(iii) For a given value of *f*, heavy users (with high $\overline{C}^h$) consume more than light users at any given inventory level. Figure 1 illustrates this by graphing the function at various values of $\overline{C}^h$ while keeping *f* fixed. The figure shows that higher $\overline{C}^h$'s move the function upwards, without changing its shape much.

(iv) The value of *f*, which we term the flexibility parameter, determines how responsive consumption is to high levels of inventory.[5] Figure 2 shows that, for a given value of $\overline{C}^h$, if *f* is negative, households tend to consume almost all that is available to them. If *f* is positive, on the other hand, households are not as flexible in their usage rate. In fact, for *f*=1, this usage rate function is quite similar to the status quo, in that households initially increase

[5] Like most non-linear functions, our usage rate function is not invariant with respect to the units of measurement. Therefore, its shape at various values of *f* should be evaluated for a range of inventory values that correspond to the data being used. Our data for yogurt and ketchup are measured in ounces, and, in the discussion that follows, we evaluate the usage rate function for inventory in multiple ounces.

consumption with inventory, but once they approach their average usage rate, $\overline{C}^h$, consumption remains constant even for high values of inventory.[6]

Thus, this usage rate function is able to map out varying levels of flexibility in consumption through the parameter *f*. Status quo models, by not allowing consumption to vary with inventory levels above $\overline{C}^h$, have essentially assumed a value of *f* equal to 1. We, on the other hand, empirically estimate the value of *f*.

2.3 Model for Brand Choice, Purchase Incidence and Purchase Quantity:

We link the choice and incidence models through a standard nested logit formulation, and incidence and quantity decisions through a hurdle formulation (Mullahy 1986).[7] While the former is standard in the literature, the latter deserves some discussion. A binomial logit model governs purchase incidence, and if the "hurdle" is crossed and a purchase takes place, the conditional distribution of the number of units purchased is governed by a truncated-at-zero Poisson model. The advantage of this hurdle formulation is that the incidence and quantity models, both of which contain the inventory variable and are therefore affected by the usage rate function, can be jointly estimated. In addition, the Poisson model, unlike regression models used in the literature, provides integer predictions of purchase quantity.

The specific formulations for brand choice, purchase incidence and purchase quantity models are described below. The explanatory variables used in each model are based on existing literature (e.g., Gupta 1988, Guadagni and Little 1983, Bucklin and Lattin 1991, Tellis and Zufryden 1995, Bucklin and Silva Risso 1996) and are detailed in the appendix.

2.3.1 Brand Choice: The probability $P^h{}_t(j|inc)$ that a household *h* will choose brand-size *j* during shopping trip *t*, given that the product category is being purchased is modeled as:[8]

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6 This can also be seen analytically by calculating the first derivative of the function at *f*=1 and taking the limit as inventory goes to ∞.

7 We thank Pradeep Chintagunta, University of Chicago, for suggesting this approach to us.

8 The brand-size choice model is required only to the extent that it provides parameters for the category value variable to be used in the incidence model.

$$P_t^h(j \mid inc) = \frac{e^{U_{jt}^h}}{\sum_{k \subset K_{st}} e^{U_{kt}^h}} \tag{5}$$

where K_{st} is the set of brand-sizes available in store *s* where the household shops on the *t*'th shopping trip, and U^h_{jt}, the systematic utility of a given brand-size, is a linear function of its shelf price per ounce, whether or not it is on promotion, and the loyalty of the household to the brand and size of brand-size j.

2.3.2 Purchase Incidence: The probability that household h will purchase the product category during shopping trip t is:

$$P_t^h(inc) = \frac{e^{V_t^h}}{1 + e^{V_t^h}} \tag{6}$$

where V^h_t, the systematic utility,is a linear function of the category value (equal to the logarithm of the denominator in equation 5, i.e., the inclusive value in nested logit), inventory (mean-centered for each household), $\overline{C}^h$, and lagged purchase incidence. We include the lagged incidence variable to model systematic swings in purchase and consumption due to eating bouts, binging, special diets, and other situational factors (see, for example, McAlister and Pessemier 1982, Logue 1991, Wansink 1994). As a result of these phenomena, category purchase on one shopping trip may be associated with higher likelihood of purchase on the next trip.[9] 2.3.3 Purchase Quantity: A truncated-at-zero Poisson model governs probability of purchasing q units ($q \geq 1$), given that the purchase incidence hurdle has been passed:

$$P_t^h(q \mid inc \& j) = \frac{(\lambda_{jt}^h)^q}{(e^{\lambda_{jt}^h} - 1)q!} \tag{7}$$

where the Poisson parameter λ^h_{jt} is a linear function of (mean-centered) inventory, the average number of units purchased by the household, denoted by $\overline{U}^h$, the size, price, and promotion status of the selected brand-size.

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[9] The key empirical results in our paper are not sensitive to whether or not lagged incidence is included in the model.

3. EMPIRICAL ANALYSIS

We estimate these models for two product categories, yogurt and ketchup. We wish to (i) determine whether the flexible usage rate phenomenon exists, by examining improvement in statistical fit over the status quo model; (ii) evaluate convergent validity by comparing results obtained from the spline and continuous usage rate functions; and (iii) evaluate discriminant validity by comparing usage rate parameters for the two product categories.

3.1 Hypotheses:

Yogurt is perishable and can be consumed as a "snack" at any time during the day. Further, since it must be refrigerated, its presence is made salient every time the refrigerator is opened. This encourages increased yogurt consumption when inventory is high. Ketchup, on the other hand, is less versatile in terms of usage occasions, and is not eaten by itself. Further, it is not perishablenor refrigerated until a bottle has been opened. There could be some flexibility due to splurging when inventory is high or holding back consumption when it is low, but it is not likely to be consumed a lot faster simply because there is extra inventory at hand. Therefore, we have the following hypotheses for the estimated usage rate parameters in the two product categories:

H1: Yogurt consumption is very flexible while ketchup is less so. Therefore, the usage rate parameters in the spline and continuous functions should be:

$1 < a_{\text{ketchup}} < a_{\text{yogurt}}$

$f_{\text{yogurt}} < 0 < f_{\text{ketchup}}$

3.2 Data:

We utilize Nielsen scanner panel data from two markets, Springfield, MO and Sioux Falls, SD. The first 51 weeks are used for initialization of $\overline{C}^h$, $\overline{U}^h$, $\overline{T}^h$, and the loyalty variables and the next 51 weeks for calibration. Since our interest is in measuring consumption of the product category, we include all available brand-sizes of the product category in our analysis. Only households who made at least one shopping trip every two weeks are included in the analysis (i.e., a "1 in 2 static" sample). Our analyses of the yogurt and ketchup categories are therefore based on 849 and 1238 households respectively. The total number of shopping trips made by these households during the calibration period is 99,344 and 141,727 respectively and the number of purchase occasions are 9964 and 5713 respectively.

3.3 Estimation Procedure

We use the maximum likelihood module in the GAUSS computer program to estimate our models. The likelihood function for the entire system of purchase incidence, brand-size choice, and quantity, described in the previous section, is given by:

$$L = \prod_h \prod_t \prod_{k \in K_{st}} \left(\frac{e^{U^h_{jt}}}{\sum e^{U^h_{kt}}}\right)^{D^h_{kt}} \left(\frac{1}{1+e^{V^h_t}}\right)^{1-D^h_t} \left(\frac{e^{V^h_t}}{1+e^{V^h_t}}\right)^{D^h_t} \left(\frac{(\lambda^h_{jt})^{q^h_t}}{(e^{\lambda^h_{jt}}-1)q^h_t\,!}\right)^{D^h_t} \tag{8}$$

where:

D^h_{kt} = a dummy variable equal to 1 if $k = j$, the brand-size purchased by household *h* on trip *t*, 0 otherwise.

D^h_t = a dummy variable equal to 1 if the product category is purchased by household *h* on trip *t*, 0 otherwise.

q^h_t = number of units purchased by household *h* on trip *t*.

The model is estimated in two steps. First we estimate the brand choice model by maximizing the log of the first element of the likelihood function, and use its estimated parameters to create the category value variable for the purchase incidence model.[10] Second we estimate the usage rate function, purchase incidence, and quantity models jointly by maximizing the log of the remaining three elements of the likelihood function.[11] The usage rate function is

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[10] In the interest of space, we do not report estimates of the brand choice model here. Details are available from the authors upon request.

[11] Although standard errors for estimates of the purchase incidence model are smaller as a result of this sequential estimation of brand choice and incidence parameters, it is very commonly used because of its computational ease (e.g., Bucklin and Lattin 1991, Tellis and Zufryden 1995). It is particularly helpful for us since it separates the brand-size choice model from the incidence and quantity models and eliminates the computational burden involved in unnecessarily estimating the brand-size choice model at every iteration of the maximum likelihood estimation of the usage rate, incidence and quantity models.

embedded in the likelihood function through the inventory variable. For comparison, we also estimate the status quo incidence and quantity models.

3.4 Results:

Table 1 displays statistical fit for the incidence and quantity models using the three usage rate specifications: (i) status quo; (ii) spline function; and (iii) continuous function. It also provides the estimated usage rate parameter for the latter two specifications and a test statistic used to compare their fit with the status quo (Ben-Akiva and Lerman 1985).

Insert Table 1 About Here

Several important points should be noted from Table 1. First, the log-likelihood and the adjusted likelihood ratio indices are higher for the two flexible usage rate models than for the status quo. For yogurt, this improvement in fit comes from both the incidence and quantity models, whereas, for ketchup, the improvement is almost entirely due to the incidence model. This is not surprising since most households buy a single bottle of ketchup per purchase occasion.

Second, the overall improvement in fit over the status quo model is highly statistically significant for both product categories and for both flexible usage rate functions. This can be seen from the magnitude of their Z-statistics (Ben-Akiva and Lerman 1985). Thus, we have strong evidence for the existence of a flexible usage rate as well as convergent validity from both the spline and continuous functions.

Third, the estimated values of the usage rate parameters strongly support our hypotheses. For the continuous function, the estimated value of f is -0.65 for yogurt and +0.90 for ketchup.[12] For the spline function, the estimated value of a is 590 for yogurt and 1.42 for

[12] As expected, the value of the log-likelihood function for the status quo model is very close to its value for our continuous usage rate model when the flexibility parameter f is set equal to 1.0.

ketchup. These parameter values confirm that yogurt usage rate increases steadily with available inventory while ketchup usage rate is less sensitive to available inventory. The standard errors of the usage rate parameters for both product categories show that the difference in estimated values is statistically significant. Thus, we obtain strong discriminant validity for both the usage rate functions. The value of *a* for yogurt, however, seems very high. The reason for this is that some households have very low values of $\overline{C}^h$ (e.g., 0.01 oz.), since they buy yogurt very infrequently. Even these infrequent users, however, consume most of their yogurt soon after purchasing it. A large *a* is the only way that the spline function can reflect this. This large *a* does not hurt model fit for frequent buyers because consumption is not allowed to exceed available inventory.

Fourth, the spline and continuous functions fit equally well in the yogurt category, but, in the ketchup category, the continuous function is significantly better.[13] Since consumption varies continuously with inventory it also decreases continuously over the time between two purchases. For product categories with very high flexibility (e.g., yogurt), households quickly consume all they have and inventory essentially goes down to zero. As we have seen above, the spline can approximate this continuous function quite well by estimating an extremely large value for *a*. Similarly, the spline will also work well for product categories with no flexibility since usage rate flattens out at $\overline{C}^h$. However, for product categories with intermediate levels of flexibility (e.g., ketchup), where consumption decreases gradually over time between two purchase occasions, this discontinuous function does not provide a good enough approximation to actual consumption.

Table 2 shows estimates of the purchase incidence and quantity model for each product category using the status quo as well as the continuous flexible usage rate function.[14] A comparison of the two sets of estimates shows that the key difference between them lies in the

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[13] The spline function actually fits better for the yogurt quantity model, but this is offset by its poorer fit for the incidence model.

[14] Estimates using the spline function are very similar.

inventory parameter. Three of the four inventory parameters are much stronger when the flexible usage rate function is used because it allows us to obtain a better measure of household inventory than that obtained by the status quo model. The exception is the ketchup quantity model, which remains insensitive to inventory because, as we have noted earlier, most households buy a single unit of ketchup. Not surprisingly, the strengthening of the inventory parameter is much more dramatic in the case of yogurt. Yogurt consumption is highly flexible and the status quo model, by enforcing a constant consumption rate, introduces a large amount of measurement error in the inventory variable, thus biasing its coefficient strongly towards zero. When this measurement error is reduced through our flexible usage rate function, we obtain a less biased, stronger inventory parameter.

Insert Table 2 About Here

3.5 Quantifying the Consumption Effect:

In order to quantify the effect of promotion on total category demand, we simulated purchases for 100 of the households in our sample over a one-year horizon using the promotional environment defined by our data and our parameter estimates based on the continuous usage rate function. The natural level of promotion observed in our data represented the "base" case. Then, we added one promotion and re-ran the simulations, thus obtaining the "promotion" case. We then compared category sales, brand sales and switching, purchase acceleration, and consumption between the promotion case and the base case. This was done for both product categories.

Figures 3 and 4 show the effect of adding a promotion for one of the brands of yogurt, in week 24, on the number of category ounces purchased and consumed by the households. There is an immediate increase in both ounces purchased and consumption, since households quickly consume all their additional inventory. The top half of Table 3 summarizes how the short-term sales bump due to promotion is decomposed. The promotion induced the purchase of 179 additional ounces of the promoted brand. Of this, approximately 65% represents sales taken from the competition, while the remaining 35% represents an increase in consumption.

Insert Figures 3 and 4, and Table 3 About Here

In contrast, Figures 5 and 6 depict what happens in the ketchup category. The additional category ounces purchased due to the promotion in week 18 are consumed much more gradually over time. The bottom half of Table 3 shows that, in the case of ketchup, only 12% of the 130 additional ounces of the promoted brand purchased is attributable to increased consumption.

Insert Figures 5 and 6 About Here

The specific percentage of the sales bump attributable to consumption depends upon the specific brand promoted, its size, and the competitive environment, and should therefore not be considered as benchmarks for these product categories. Still, the simulations clearly show that the consumption effect of promotion is quite significant for products where usage rate is highly responsive to inventory levels.

4. DISCUSSION

In summary, we have accomplished the following in this paper:

(i) We have captured the usage rate mechanism by which promotion can increase category demand. We have done so by modeling consumption during a given period as a function of inventory at the beginning of that period and incorporating this into a jointly estimated purchase incidence and quantity model. We have tested two different functional forms for this flexible usage rate.

(ii) We have estimated these models for two product categories, yogurt and ketchup, and shown that, in both cases, flexible usage rate functions fit significantly better than the status quo model. Convergent validity is evidenced by the ability of both functions to model the flexible usage rate phenomenon.

(iii) Discriminant validity is provided by the ability of both functions to estimate significantly different usage rate parameters for the less flexible ketchup category and the more flexible yogurt category.

(iv) The importance of the flexible usage rate phenomenon is also demonstrated by quantifying the effect of promotion on consumption through Monte Carlo simulation. For yogurt, where usage rate is highly flexible, a substantial percentage of the short term promotion sales bump is attributable to increased category consumption

4.2 Implications for Researchers and Managers:

There are several implications of these results for researchers. First and most basically, flexible consumption is a real phenomenon that provides a fertile area for marketing science modeling. There are many more issues to investigate. For instance, which product categories are more or less prone to flexible consumption, and why? We believe our results illustrate the promise of undertaking such work.

Second, our flexible usage rate functions appear to capture the phenomenon quite well with only one parameter. The continuous function is preferred since it fits as well as the spline in one category and significantly better in the other. However, there are various avenues along which these functions could be improved. For example, the parameters in the two usage rate functions, *a* and *f*, could in turn be a function of price expectations, and/or could depend on various demographics such as household size and income level. One could also investigate household heterogeneity in these parameters by splitting the data by demographic group and estimating a separate parameter for each, or by using one of several methods of modeling unobserved heterogeneity (e.g., Kamakura and Russell 1989, Chintagunta, Jain and Vilcassim 1991).

Third, we need to understand the behavioral underpinnings of flexible consumption in more detail. For instance, our model establishes a strong link between inventory and consumption. But, it does not speak to whether households jointly optimize inventory and consumption levels or whether promotion leads them to stockpile and they then use up additional inventory at a faster rate then usual. Further research is required to disentangle the two, be it through econometric modeling or experimental work. It would also be valuable to develop a comprehensive utility maximization framework that brings together work by researchers like Chintagunta (1993) and Chiang (1991) on optimal *purchase* decisions with work on optimal *consumption* decisions by researchers like Assuncao and Meyer (1993).

Our work also has important implications for managers. Managers should not view promotion only as a market share or temporal displacement game. It can be used to grow the category. This is particularly important for managers of high share brands who often view promotion as unprofitable because they cannot attract much more share. Of course, as we have seen, this depends on the product category. Staples such as bathroom tissue, diapers, and various cleaning products might be difficult to expand with promotion. But for many other categories - yogurt, cereal, cookies, beverages, etc. - perhaps managers should think of promotion as a tool for growing the category rather than only as a market share weapon. Finally, there may also be some important public health and policy implications of this research, especially as it relates to consumption of food items and diet control.

TABLE 1
STATISTICAL FIT OF ALTERNATIVE CONSUMPTION FUNCTIONS

	Yogurt			Ketchup		
	Status Quo	**Spline**	**Continuous**	**Status Quo**	**Spline**	**Continuous**
No. of Observations	99344	99344	99344	141727	141727	141727
Purchase Incidence Model:						
Log Likelihood	-29418.91	-29403.14	-29389.15	-22410.05	-22373.45	-22294.36
Null Log Likelihood*	-32095.96	-32095.96	-32095.96	-23754.30	-23754.30	-23754.30
$\bar{\rho}^2$	0.0833	0.0837	0.0842	0.0564	0.0579	0.0612
Purchase Quantity Model:						
Log Likelihood	-8497.81	-8389.66	-8402.35	-189.03	-189.00	-188.89
Null Log Likelihood*	-10145.51	-10145.51	-10145.51	-206.36	-206.36	-206.36
$\bar{\rho}^2$	0.1619	0.1726	0.1713	0.0599	0.0551	0.0556
Overall Model:						
Usage Rate Parameter	____	590.00 (140.78)	-0.650 (0.063)	____	1.42 (0.04)	0.900 (0.005)
Log Likelihood	-37916.72	-37792.80	-37791.50	-22599.08	-22562.45	-22483.25
Null Log Likelihood*	-42241.47	-42241.47	-42241.47	-23960.66	-23960.66	-23960.66
$\bar{\rho}^2$	0.102	0.105	0.105	0.056	0.058	0.061
Z-statistic		-15.71	-15.80		-8.50	-15.19

* The null model contains only the constant term.

TABLE 2
MODEL ESTIMATES UNDER ALTERNATIVE CONSUMPTION FUNCTIONS

Variable	Yogurt		Ketchup	
	Status Quo	Flexible Usage (Continuous)	Status Quo	Flexible Usage (Continuous)
Purchase Incidence Estimates:				
$\overline{C}^h$	0.271* (0.007)	0.266* (0.005)	0.989* (0.022)	0.994* (0.023)
Category Value	0.050* (0.018)	0.052* (0.018)	0.062* (0.020)	0.061* (0.021)
Inventory	-0.0003* (0.0001)	-0.015* (0.002)	-0.015* (0.001)	-0.024* (0.001)
Lagged Incidence	1.336* (0.027)	1.412* (0.028)	-0.110 (0.072)	0.123** (0.073)
Purchase Quantity Estimates:				
Inventory	0.0001* (0.00004)	-0.012* (0.001)	-0.0005 (0.0004)	-0.0009 (0.002)
$\overline{U}^h$	0.156* (0.004)	0.152* (0.003)	0.318* (0.053)	0.317* (0.081)
Size Purchased	-0.042* (0.002)	-0.042* (0.003)	-0.001 (0.002)	-0.001 (0.015)
Price	-3.277* (0.260)	-3.692* (0.268)	-1.201 (1.404)	-1.201 (6.900)
Promotion	0.133* (0.015)	0.122* (0.014)	0.021 (0.028)	0.021 (0.111)

Note: Standard errors are in parentheses
* $p<0.05$ ** $p<0.10$

TABLE 3
SUMMARY OF SIMULATION RESULTS

Difference Between Base and Promotion Case: Yogurt

	Category	Brand	Competition
Ounces Purchased	64.10	179.43	-115.33
Ounces Consumed	63.96 which is: 35% ± 10.4% of the total brand effect* 30% ± 5.6% increase over average weekly consumption*		

Difference Between Base and Promotion Case: Ketchup

	Category	Brand	Competition
Ounces Purchased	23.29	130.48	-107.20
Ounces Consumed	16.39 which is: 12% ± 5.8% of total brand effect* 11.5% ± 3.3% increase over average weekly consumption*		

* This is a 95% confidence interval based on 100 replications of the simulation

FIGURE 1: EFFECT OF $\overline{C}^h$
(*f*=1.0)

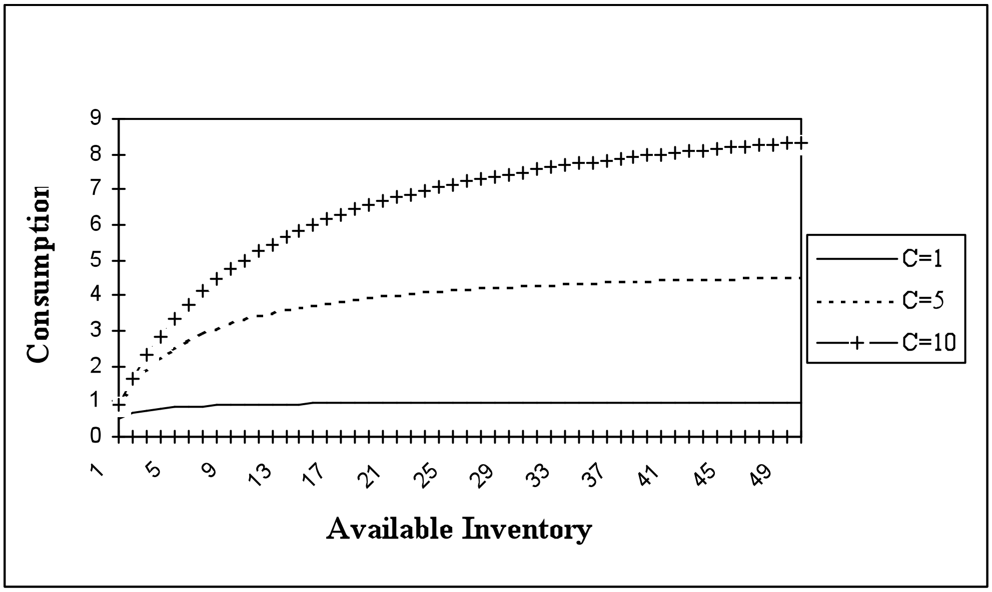


FIGURE 2: EFFECT OF FLEXIBILITY PARAMETER *f*
($\overline{C}^h$ =2)

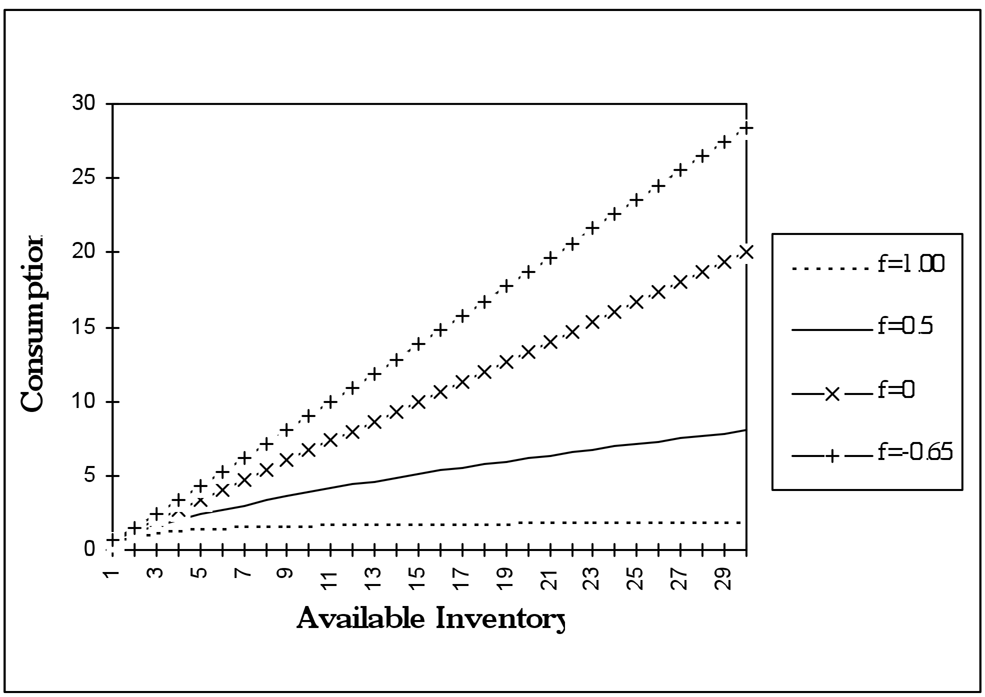


Figure 3
Yogurt Category Ounces Purchased:
Promotion Vs. Base Case
(Promotion for Brand C Yogurt, Week 24)

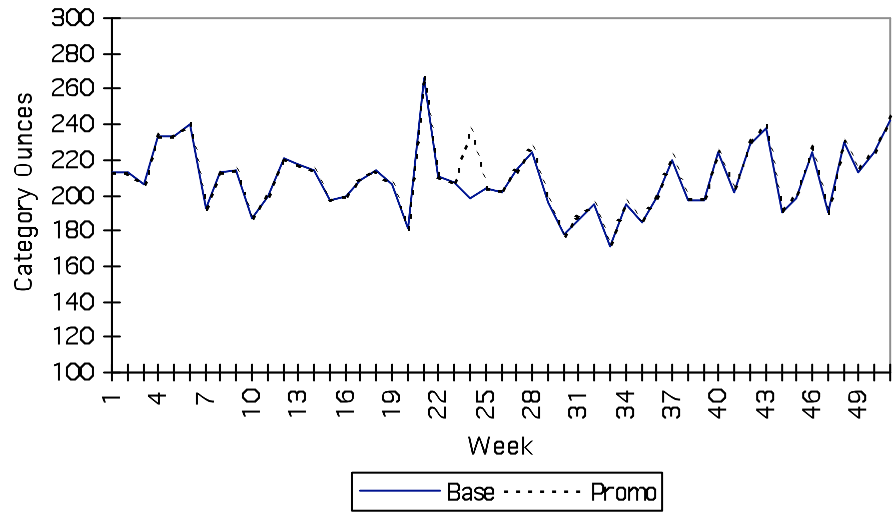


Figure 4
Yogurt Category Ounces Consumed:
Promotion Versus Base Case
(Promotion for Brand C Yogurt, Week 24)

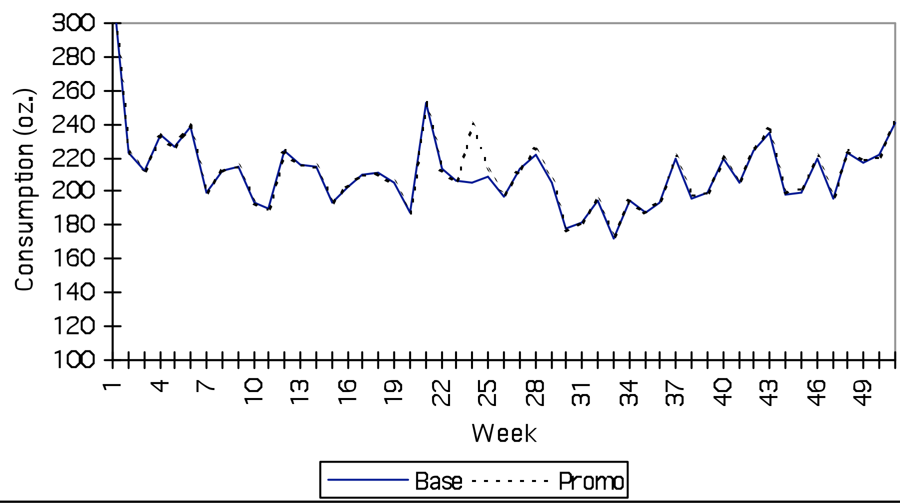


Figure 5
Ketchup Category Ounces Purchased: Promotion Vs. Base Case
(Promotion for Brand A in Week 18)

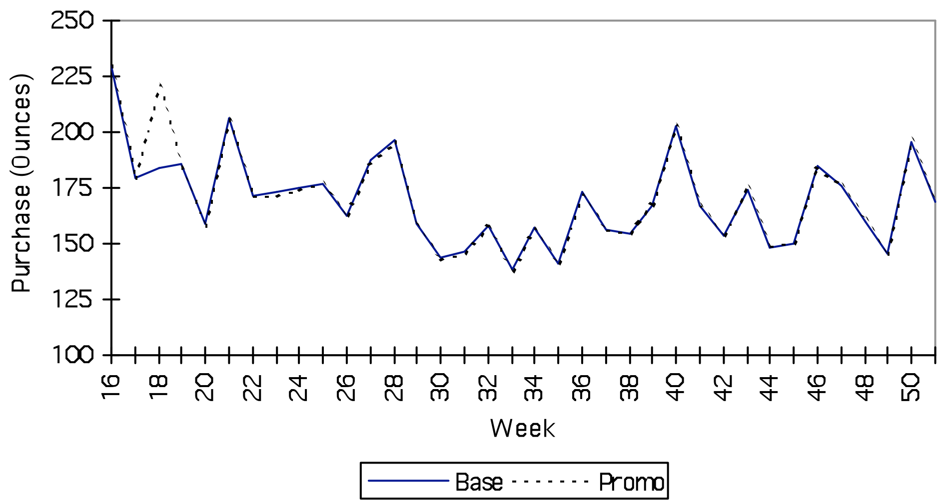
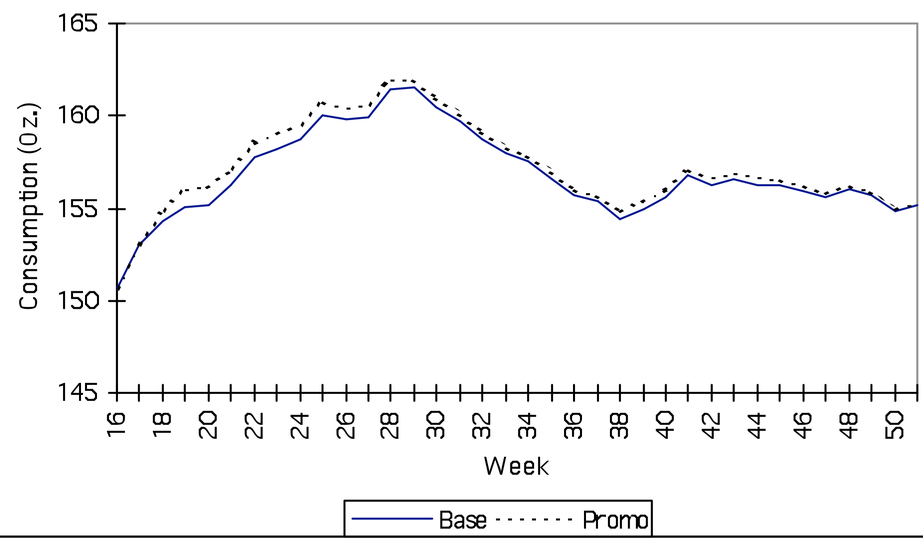


Figure 6
Ketchup Category Consumption: Promotion Vs. Base Case
(Promotion of Brand A Ketchup in Week 18)



APPENDIX
VARIABLES IN INCIDENCE, CHOICE AND QUANTITY MODELS

Purchase Incidence:

$$V'^{h}_{t} = V^{h}_{t} + \varepsilon^{h}_{t} \quad \text{(A1)}$$

$$V^{h}_{t} = \beta_0 + \beta_1 CatVal^{h}_{t} + \beta_2 Invn^{h}_{t} + \beta_3 \overline{C}^{h} + \beta_4 PurInc^{h}_{t-1} \quad \text{(A2)}$$

$CatVal^{h}_{t}$ = Category Value for household *h* during week *t* (equal to the "inclusive value" of nested logit, obtained from the brand choice model);

$Invn^{h}_{t}$ = Mean centered inventory held by household *h* at beginning of week *t*;

$\overline{C}^{h}$ = Average daily consumption for household *h*, equal to total amount purchased over the period divided by number of days;

$PurInc^{h}_{t-1}$ = Dummy variable equal to 1 if product category was purchased during previous shopping trip and 0 if not.

Brand Choice:

$$U'^{h}_{jt} = U^{h}_{jt} + \varepsilon^{h}_{jt} \quad \text{(A3)}$$

$$U^{h}_{jt} = \beta_{0j} + \beta_1 \Pr ice^{h}_{jt} + \beta_2 \Pr omo^{h}_{jt} + \beta_3 Bloy^{h}_{jt} + \beta_4 Sloy^{h}_{jt} \quad \text{(A4)}$$

where:

K_{st} = Set of brand-sizes available in store *s* where the household shops on the *t*'th shopping trip.

$Price^{h}_{jt}$ = Shelf price per ounce of brand size *j* (including discounts) on trip *t* in the store visited by household *h*.

$Promo^{h}_{jt}$ = 1 if brand-size *j* is featured or displayed on trip *t* in the store visited by household *h*.

$Bloy^{h}_{jt}$ = Loyalty of household *h* for the brand of brand-size *j* at beginning of trip *t*.

$Sloy^{h}_{jt}$ = Loyalty of household *h* for the size of brand-size *j* at beginning of trip *t*.

Purchase Quantity:

$$\lambda_{jt}^{h} = \beta_0 + \beta_1 Invn_t^h + \beta_2 \overline{U}^h + \beta_3 Size_j + \beta_4 \operatorname{Pr}ice_{jt} + \beta_5 \operatorname{Pr}omo_{jt} \tag{A5}$$

where:

$Invn^h_t$ = Mean-centered inventory held by household *h* at the beginning of the t'th trip.

$\overline{U}^h$ = Average number of units purchased by household *h*.

$Size_j$ = Size (in ounces) of the chosen brand-size *j*.

$Price^h_{jt}$ = Price per ounce for the selected brand-size *j* in the store visited by household *h* on the *t*'th trip.

$Promo^h_{jn}$ = 1 if the selected brand-size *j* is featured or displayed on trip *t* in the store visited by household *h*.

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