Reprinted with permission from the *Journal of Marketing Research*, published by the American Marketing Association, Kamel Jedidi, Carl F. Mela, and Douglas Bowman, Vol. 35, no. 2 (May 1998), 250-62.

CARL F. MELA, KAMEL JEDIDI, and DOUGLAS BOWMAN*

Although brands have increased their promotional spending substantially in many categories over the past decade, panel-based research into consumer stockpiling behavior typically has assumed that consumers' decisions regarding whether and how much to purchase have remained invariant to this increase. The authors develop a varying parameter model of purchase incidence and purchase quantity to ascertain whether this increase in promotions has affected households' stockpiling decisions in the long term. The authors estimate the model on the basis of more than eight years of panel data for a frequently purchased, nonfood, consumer packaged-goods product. The results suggest that consumers' stockpiling behavior has changed over the years. The increased long-term exposure of households to promotions has reduced their likelihood of making category purchases on subsequent shopping trips. However, when households do decide to buy, they tend to buy more of a good. Such behavior is indicative of an increasing tendency to "lie in wait" for especially good promotions. This change appears to have some deleterious ramifications for category profitability.

The Long-Term Impact of Promotions on Consumer Stockpiling Behavior

Consumer packaged-goods firms spend approximately $70 billion annually on trade promotions (*Progressive Grocer* 1995). Moreover, many of these firms have been increasing the proportion of their marketing budget spent on trade promotions; more than 70% of manufacturers increased promotional expenditures between 1990 and 1995. Consumer and trade promotions now account for 50% of many manufacturers' marketing budgets. This increase comes in spite of efforts by some major consumer packaged-goods companies to reduce their promotional expenditures (*Forbes* 1991) and/or cut their couponing efforts (*The Wall Street Journal* 1996). The reason for increasing promotional spending is clear: Promotions have a large, measurable, immediate effect on a brand's sales (Blattberg and Neslin 1989).[1]

In spite of the substantial, temporary increase in household purchases attributable to the use of promotions, there are concerns that such promotions might have a differing long-term effect. For example, in categories in which promotions have become frequent, consumers might learn to anticipate future deals. This particular scenario suggests that (1) a particular promotional event induces a household to stockpile[2] on a given purchase occasion (short-term effect), followed by (2) the promotion's long-term, negative effect, which is manifested as an increased probability that the household waits for another promotion before buying on subsequent purchase occasions.

Consistent with the spirit of the foregoing example, we define a *short-term promotional effect* as an immediate response to a promotion on a particular shopping visit (single point in time). In contrast, a *long-term effect* refers to the cumulative effect of previous promotional exposures (over quarters or years) on a consumer's current, or short-term, decision of whether and how much to buy. The effect of past exposures on current purchases also suggests a carryover effect; a promotion in the current period will affect behavior in subsequent periods. Because the duration of these promo-

[1]By *promotions*, we refer to features, displays, coupons, and temporary price reductions. Here, we use *promotion* interchangeably with *deals* because these promotions often are accompanied by price reductions.

*Carl F. Mela is Assistant Professor of Marketing, College of Business Administration, University of Notre Dame (e-mail: carl.f.mela.1@nd.edu). Kamel Jedidi is Associate Professor of Marketing, Graduate School of Business, Columbia University (e-mail: kj7@columbia.edu). Douglas Bowman is Assistant Professor of Marketing, Krannert Graduate School of Management, Purdue University (e-mail: bowman@mgmt.purdue.edu). The authors thank the editor and the former editor, four anonymous *JMR* reviewers, Rebecca Mela, Scott Neslin, and Joe Urbany for their helpful comments and Information Resources Inc. and an anonymous consumer packaged-goods company for their financial assistance and discussions.

[2]*Stockpiling* is defined as buying larger quantities of a product and/or shifting purchase times to buy before the expected time of next purchase (Blattberg and Neslin 1990). Ailawadi and Neslin (1998) suggest that *stockpiling* is distinct from *category expansion* because, with stockpiling, consumers compensate for buying more by making fewer purchases or purchasing smaller quantities in the future. Although our focus is on the former, we also offer insights into the latter.

tional effects can be substantial (quarters or years), they are considered to be long term (Blattberg and Neslin 1989; Fader et al. 1992).[3]

Although there recently have been a few studies that have examined the long-term effect of promotions on choice, share, or sales (Boulding, Lee, and Staelin 1994; Dekimpe and Hanssens 1995a, b; Lal and Padmanabhan 1995; Mela, Gupta, and Jedidi 1998; Mela, Gupta, and Lehmann 1997; Papatla and Krishnamurthi 1996), few, if any, studies have examined the long-term impact of promotions on stockpiling. Doing so is particularly important because Blattberg, Briesch, and Fox (1995) argue that, in some categories, the effects of promotions on incidence and quantity are even greater than they are on choice. Therefore, the primary goal of this article is to examine the long-term impact of promotions on consumers' stockpiling decisions. Specifically, we seek to answer the following array of questions: Are consumers more or less likely to make a category purchase in the absence of promotions in response to an increase in the use of promotions by manufacturers? Given a decision to buy, are they more or less likely to buy larger quantities? What are these effect sizes, if any? For example, would the negative long-term effect of a promotion outweigh the incentive to buy that it provides in the current period?

The article is organized as follows. We begin by developing hypotheses. We then develop a varying parameter model of category incidence and purchase quantity, as well as an estimation procedure that enables us to assess how household stockpiling behavior changes over time. Next, we describe our data, variable operationalization, and the model specification used to test our hypotheses. The data section is followed by a presentation of the results and a discussion of their implications. We conclude with a summary of our contributions and directions for further research.

The Effect of Promotions on Consumer Stockpiling

Both reference pricing theories (Bell and Bucklin 1996; Jacobson and Obermiller 1990; Kalyanaram and Winer 1995) and inventory management models (Assunçao and Meyer 1993; Helsen and Schmittlein 1992; Krishna 1992, 1994) make predictions regarding the long-term effect of promotions on stockpiling. However, these models often are estimated or predicated on shorter periods of data or fewer purchase cycles than we seek to analyze. Furthermore, these models do not partial the short- and long-term effects of promotions explicitly, nor do they disentangle purchase incidence and quantity effects directly. Concurrently modeling the decisions of whether and how much to buy (conditioned on incidence) offers additional insights over modeling expected purchase quantities alone (the product of incidence probabilities and conditional purchase quantities).

For example, consumers might reduce their incidence probabilities and increase their conditional purchase quantities (i.e., they might *lie in wait* for especially good deals). Such a strategy could yield constant expected purchase quantities even in the face of radically different stockpiling behavior. Solely modeling expected purchase quantities cannot capture this change because expected purchase quantities would remain constant over time. The foregoing scenario therefore suggests that it is important to model the incidence and quantity decisions jointly and to capture any potential dependence that might exist between these decisions. The example also implicitly suggests why it is important to disentangle promotion's short- and long-term effects, as they might be very different. In the short term, a promotion increases sales in the week it is offered. In the long term, it might train consumers to lie in wait for a good deal.

Purchase incidence decision. Reduced incidence probabilities are one component of a lying-in-wait heuristic (along with higher conditional purchase quantities), and there are several theories that suggest that a household's long-term exposure to promotions could reduce incidence probabilities. Reference price models suggest that increased discounting on previous purchase occasions results in lower reference prices on the current purchase occasion. Using this theory, Bell and Bucklin (1996) develop a "sticker shock" model of category purchase incidence. In their model, increased promotional exposure on prior store visits increases the reference "value" for the product category on the current store visit. Consequently, the difference between the category value and the reference value diminishes, which results in a reduced likelihood of a category purchase incidence. Therefore, increased long-term exposure to promotions might lead to a lower category purchase incidence probability on subsequent purchase occasions.

Future price expectations (as opposed to reference price) also affect stockpiling. Gönül and Srinivasan (1996) show that consumers develop expectations about coupon availability and further suggest that these expectations of coupons in future periods lead consumers to defer purchases on subsequent occasions. Jacobson and Obermiller (1990) also argue that past prices affect expectations regarding future prices. Analyzing five categories, they find that current purchase is discouraged by expectations of lower prices in the future. Consequently, we hypothesize the following:

H_1: Increased long-term exposure to promotions leads to lower off-deal purchase incidence probabilities.

Normative household inventory management models (Assunçao and Meyer 1993; Helsen and Schmittlein 1992; Krishna 1992, 1994) make several further predictions regarding the long-term effect of promotions on incidence behavior. These models suggest that consumers trade off the savings from purchasing on promotion with the added cost of stockpiling extra inventory. The use of promotions is a critical component in how this trade-off is made. Helsen and Schmittlein (1992) argue that consumers' reservation prices for making a category purchase drop as they are exposed to more promotions. Hence, as promotions become endemic, increasingly big promotions are needed to stimulate a purchase. Therefore, consumers forego many of the discounts and appear to be less promotion sensitive. Assunçao and Meyer (1993) echo this reasoning. They hypothesize that increasing expectations of a better deal in the near future increases the likelihood of foregoing a deal in the current period (resulting in lower promotion sensitivity). We therefore hypothesize the following:

H_2: Increased long-term exposure to promotions leads to lower (less positive) purchase incidence promotion sensitivity.

[3]Not all long-term effects (Blattberg and Neslin 1989; Fader et al. 1992) can be considered persistent (Dekimpe and Hanssens 1995a, b). Our definition of long-term effects includes effects that decay over time (albeit over quarters or years). Persistent effects are permanent and enduring.

Kalyanaram and Winer (1995) reason that, over time, promotions erode purchase probabilities by lowering reference prices and thereby increasing price sensitivity. As a result, consumers might be more reluctant to pay regular prices or tolerate price increases. Such arguments are consistent with a lie-in-wait strategy, in which consumers are less likely to buy at high prices as they learn to buy when prices are especially low. Therefore,

H_3: Increased long-term exposure to promotions leads to higher (more negative) purchase incidence price sensitivity.

The normative inventory management models also offer predictions regarding how increased promotions affect inventory sensitivity in the purchase incidence decision. Krishna (1992) suggests that, especially when promotions are common and inventory is high, households might be less likely to make a purchase. Gönül and Srinivasan (1996) show that households with excess inventory are more likely to defer purchases if the expectation of future promotion availability is high. We therefore hypothesize the following:

H_4: Increased long-term exposure to promotions makes consumers more sensitive to inventory levels in their purchase incidence decision (i.e., inventory sensitivity becomes more negative).

Purchase quantity decision. There are few prior research studies that lend direct theoretical or empirical insight into how promotions might affect category purchase quantities *when conditioned on incidence* (conversely, most prior research reviews the effect of increased promotional frequency on expected quantity, that is, the product of incidence and quantity conditioned on incidence). Helsen and Schmittlein (1992) and Assunçao and Meyer (1993) contend that consumers who are exposed to frequent promotions are only likely to buy in a category (purchase incidence) when there is a deep discount. Similarly, Krishna (1994) shows that consumer certainty and learning regarding future promotions results in consumers who wait for promotions to buy and then buy all the quantity necessary on those purchase occasions. Such reductions in incidence probabilities (see also H_1), coupled with increases in mean purchase quantities, would be indicative of a lying-in-wait heuristic. This strategy suggests that consumers learn to anticipate and react to good promotions. On finding one, they are more likely to purchase in the category and in larger amounts. Such patterns are likely to be especially common in categories in which consumption is relatively constant and goods are nonperishable—if consumers are buying less often, they must buy greater quantities when they make purchases. Accordingly,

H_5: Increased long-term exposure to promotions leads to higher purchase quantities conditioned on purchase incidence.

Our expectations regarding the anticipated long-term effect of promotions on conditional purchase quantity price and promotion sensitivities are more speculative. Because increases in long-term promotional exposure lead consumers to lie in wait for promotions and then buy larger amounts, we expect them to become increasingly price and promotion sensitive in their conditional quantity decision. Consistent with this assertion is Assunçao and Meyer's (1993, p. 528) observation that, when promotional frequency increases, "greater purchases at deal prices and fewer purchases at regular prices ... inflate the apparent short-term relationship between price and purchase." Analogous reasoning holds for promotion sensitivity. Therefore,

H_6: Increased long-term exposure to promotions leads to higher (more positive) conditional purchase quantity promotion sensitivity.

H_7: Increased long-term exposure to promotions leads to higher (more negative) conditional purchase quantity price sensitivity.

We expect little difference between the quantity and incidence decisions regarding the importance of inventory. Should promotions become increasingly common, households might become increasingly disinclined to buy large quantities when the product is already in inventory. Therefore, similar to H_4, we expect that

H_8: Increased long-term exposure to promotions makes consumers more sensitive to inventory levels in their purchase quantity decision (i.e., inventory sensitivity becomes more negative).

The central thesis of these hypotheses is that past promotions affect current behavior and that consumers adapt to changes in their promotional environment. Yet econometric models of stockpiling behavior typically have assumed that household response parameters are invariant to marketing policy. Erdem and Keane (1996) denote such models "reduced form" and argue that they can lead to erroneous inferences regarding consumer behavior. We now outline a modeling approach that relaxes the assumptions of invariant household response parameters and enables us to assess whether stockpiling behavior indeed is affected by long-term exposure to promotions.

METHODOLOGY

Overview

To test our hypotheses, we develop a joint model of incidence and purchase quantity that has the following features:

- Category incidence is modeled as a function of marketing variables (e.g., price) and household-specific variables (e.g., inventory), using a probit framework.
- The incidence response parameters (e.g., price response) are modeled as a function of long-term exposure to marketing activity (e.g., past exposure to promotions).
- Purchase quantity is modeled as a function of marketing and household-specific variables, using a regression framework.
- The response parameters in the quantity model vary with long-term exposure to marketing activity.
- The purchase incidence and quantity decisions are dependent.

Methodologically, we extend the switching regression model in econometrics (cf. Maddala 1983, p. 223; Nelson 1977) by reparameterizing the model's coefficients as a function of long-term marketing activity. This generalization enables us to capture the dynamics of consumer responses to marketing activity over time.

Purchase Incidence Model

Nonpurchases result from a decision not to buy, not necessarily from zero desired purchase quantity (Maddala 1985, 1991). We assume a latent utility value, U_{it}, underly-

ing a household i's category purchase decision at time t. The utility value is specified as a function of observable marketing actions and household characteristics. Algebraically, household i decides to buy if the utility from buying exceeds a threshold. That is,

$$(1) \qquad U_{it} = \beta^{I}_{0it} + \sum_{m=1}^{M} \beta^{I}_{mit} x^{I}_{mit} + \varepsilon^{I}_{it} > \lambda_{it},$$

where superscript I is used to denote purchase incidence, x^{I}_{mit} is the value of explanatory variable m for household i at time t, β^{I}_{mit} is the effect of the mth explanatory variable for household i at time t on the utility value, and ε^{I}_{it} is an error term ~ $N\left[0, \left(\sigma^{I}_{0}\right)^2\right]$. λ_{it} represents a latent purchase utility threshold above which a household will decide to buy. Note that λ_{it} is not estimable because it can be absorbed into the intercept β^{I}_{0it}. Hereafter, we set $\lambda_{it} = 0$ without a loss of generality.

Next, we reparameterize each of the β^{I}_{mit} (including the intercept) as a function of J moderating variables to capture the long-term impact of marketing activities (e.g., past exposure to promotions). That is,

$$(2) \qquad \beta^{I}_{mit} = \gamma^{I}_{m0} + \sum_{j=1}^{J} \gamma^{I}_{mj} z^{I}_{ijt} + \nu^{I}_{mit};$$

$$\nu^{I}_{mit} \sim N\left[0, \left(\sigma^{I}_{m}\right)^2\right],$$

where z^{I}_{ijt} is the value of moderating variable j for household i at time t, γ^{I}_{mj} is the moderating impact of the jth variable on the mth sensitivity parameter (including m = 0 or the intercept), and ν^{I}_{mit} is an error term that reflects the inability of the moderating variables to fully explain the response parameters.[4]

Substituting Equation 2 in 1, we therefore observe a purchase if

$$(3) \qquad U_{it} = \left(\gamma^{I}_{00} + \sum_{j=1}^{J} \gamma^{I}_{0j} z^{I}_{ijt}\right) x^{I}_{0it} + \sum_{m=1}^{M} \left(\gamma^{I}_{m0} + \sum_{j=1}^{J} \gamma^{I}_{mj} z^{I}_{ijt}\right) x^{I}_{mit} + \zeta^{I}_{it} > 0,$$

where

$$(4) \qquad \zeta^{I}_{it} = \sum_{m=0}^{M} \nu^{I}_{mit} x^{I}_{mit} + \epsilon^{I}_{it}$$

is the overall error term for the purchase incidence model and $x^{I}_{0it} = 1$ (intercept). The first bracketed expression in Equation 3 reflects the varying intercept (alternatively, the main effect of the z^{I}_{ijt}), and the second represents the varying slopes. Given our distributional assumptions, ζ^{I}_{it} is normally distributed with zero mean and variance

$$\left(\sigma^{I}_{it}\right)^2 = \sum_{p=0}^{M} \sum_{\substack{r=0 \\ p \neq r}}^{M} \left(x^{I}_{pit} x^{I}_{rit}\right) \sigma^{I}_{pr} + \sum_{m=0}^{M} \left(x^{I}_{mit}\right)^2 \left(\sigma^{I}_{m}\right)^2,$$

where σ^{I}_{pr} is the covariance between the rth and pth varying incidence model parameters.

Purchase Quantity Model

We model purchase quantity as a function of a set of explanatory variables. Algebraically,

$$(5) \qquad Q_{it} = \beta^{q}_{0it} + \sum_{l=1}^{L} \beta^{q}_{lit} x^{q}_{lit} + \varepsilon^{q}_{it};$$

$$\varepsilon^{q}_{it} \sim \text{iid } N\left[0, \left(\sigma^{q}_{0}\right)^2\right],$$

where superscript q is used to distinguish the variables and parameters in the purchase quantity model from the purchase incidence model, Q_{it} is the quantity household i purchased at time t, x^{q}_{lit} is the value of explanatory variable l for household i at time t, β^{q}_{lit} is the effect of the lth explanatory variable for households i at time t, and ε^{q}_{it} is an error term.

As in the incidence model, we reparameterize the β^{q}_{lit} as a function of the moderating factors hypothesized to affect these sensitivity parameters. Specifically,

$$(6) \qquad \beta^{q}_{lit} = \gamma^{q}_{l0} + \sum_{k=1}^{K} \gamma^{q}_{lk} z^{q}_{ikt} + \nu^{q}_{lit};$$

$$\nu^{q}_{lit} \sim N\left[0, \left(\sigma^{q}_{l}\right)^2\right],$$

where z^{q}_{ikt} is the value of moderating variable k for household i at time t, γ^{q}_{lk} is the moderating impact of variable z^{q}_{ikt} on β^{q}_{lit}, and ν^{q}_{lit} is an error term that captures the inability of the z^{q}_{ikt} to fully explain the β^{q}_{lit}.

Substituting Equation 6 in 5, the purchase quantity then is expressed as

$$(7) \qquad Q_{it} = \left(\gamma^{q}_{00} + \sum_{k=1}^{K} \gamma^{q}_{0k} z^{q}_{ikt}\right) x^{q}_{0it} + \sum_{l=1}^{L} \left(\gamma^{q}_{l0} + \sum_{k=1}^{K} \gamma^{q}_{lk} z^{q}_{ikt}\right) x^{q}_{lit} + \zeta^{q}_{it},$$

where

$$(8) \qquad \zeta^{q}_{it} = \sum_{l=0}^{L} \nu^{q}_{lit} x^{q}_{lit} + \epsilon^{q}_{it}$$

is an overall error term combining error in coefficients, error in specification, and $x^{q}_{0it} = 1$(intercept).

[4]Equation 2 (and subsequently, Equation 6) controls for heterogeneity in the manner suggested by Papatla and Krishnamurthi (1996). In their approach, the γ^{I}_{m0it} are assumed to have a deterministic component ($\bar{\gamma}^{I}_{m0}$) and an error component (ω^{I}_{mit}) that captures heterogeneity in the population. That is, $\gamma^{I}_{m0it} = \bar{\gamma}^{I}_{m0} + \omega^{I}_{mit}$. The error in Equation 2 therefore can be interpreted as $\nu^{I}_{mit} = e^{I}_{mit} + \omega^{I}_{mit}$, where ω^{I}_{mit} captures heterogeneity and e^{I}_{mit} represents error arising from other sources. The intercept in Equation 2 can be interpreted as $\bar{\gamma}^{I}_{m0}$. Papatla and Krishnamurthi (1996) set the variance of e^{I}_{mit} to unity.

Our distributional assumptions lead to a ζ_{it}^{q} with a mean of zero and variance

$$\left(\sigma_{it}^{q}\right)^2 = \sum_{\substack{p=0 \\ p \neq r}}^{L} \sum_{r=0}^{L} \left(x_{pit}^{q} x_{rit}^{q}\right)\sigma_{pr}^{q} + \sum_{l=0}^{L} \left(x_{lit}^{q}\right)^2 \left(\sigma_{l}^{q}\right)^2,$$

where σ_{pr}^{q} is the covariance between the rth and pth varying parameters in the quantity model.

Joint Model

Combining Equations 3 and 7, we can write the joint model as

$$(9) \qquad Q_{it} = \sum_{l=0}^{L}\left(\sum_{k=0}^{K} \gamma_{lk}^{q} z_{ikt}^{q}\right) x_{lit}^{q} + \zeta_{it}^{q} \quad \text{if}$$

$$U_{it} = \sum_{m=0}^{M}\left(\sum_{j=0}^{J} \gamma_{mj}^{I} z_{ijt}^{I}\right) x_{mit}^{I} + \zeta_{it}^{I} > 0,$$

where the joint vector $\left\{\zeta_{it}^{q}, \zeta_{it}^{I}\right\}$ follows a bivariate normal distribution with zero mean vector and covariance matrix

$$(10) \qquad \sum_{it} = \begin{bmatrix} \left(\sigma_{it}^{q}\right)^2 & \sigma_{it}^{qI} \\ \sigma_{it}^{qI} & \left(\sigma_{it}^{I}\right)^2 \end{bmatrix},$$

where

$$\sigma_{it}^{qI} = \sum_{l=0}^{L} \sum_{m=0}^{M} x_{lit}^{q} x_{mit}^{I} \sigma_{lm}^{qI}$$

is the covariance of ζ_{it}^{I} and ζ_{it}^{q} that captures the dependence between purchase incidence and purchase quantity. The σ_{lm}^{qI} represents the covariance between the lth quantity parameter error and the mth incidence parameter error.

Several important features of the error structure should be noted. First, the error terms of the varying parameters in the incidence and purchase quantity models are correlated. Second, as suggested by Lee and Trost (1978) and Krishnamurthi and Raj (1988), the error terms in the incidence model are correlated with those in the quantity model to capture the dependence between the two decisions. Third, the parameter errors induce heteroscedasticity in both the incidence and quantity models. Fourth, we assume the errors to be serially independent in order to enhance the tractability of the model. This assumption is commonly employed in varying parameter models (e.g., Papatla and Krishnamurthi 1996). (The estimation procedure for the joint model in Equation 9 is available from the first author.)

DATA

The data used in this study are from an Information Resources Inc. static panel of 1590 households during a period of eight years. The households were located in a small midwestern city. The data, which were purchased by a large consumer packaged-goods firm, contain shopping trip and store data. The product is a frequently purchased, nonfood product. We cannot reveal the specific category because of confidentiality agreements with the firm, but the product is a nonperishable staple, such as cleaning products. Eight brands in the category account for 90% of the purchases. More than 92% of the households purchased multiple brands over the duration of the data. Consistent with previous studies (Chintagunta 1993; Gupta 1988), we sampled approximately 100 households for analysis (by randomly selecting approximately one-fifteenth of the total households yielding a sample of exactly 109 households). Our unit of analysis is a shopping trip by a household. We observe whether they make a purchase in the category and, if so, the quantity purchased. The model is calibrated on 105,515 store visits and 3866 purchases made by these 109 households. The purchase frequency of this category is similar to that of other categories used in recent research (Papatla and Krishnamurthi 1996).

Operationalization of Variables

Price, promotion, and inventory. Category price (PRICE) was formed from brand-level shelf prices[5] through a brand-share weighted average of brand prices. Category-level promotion (PROM) similarly was formed from brand-level promotions through a brand-share weighted average of brand promotions. These brand-share weights were calculated at the household level (Dillon and Gupta 1996; Gupta 1991; Jain and Vilcassim 1991) during the entire sample period. Similar to Boulding, Lee, and Staelin (1994), Bucklin and Lattin (1991), Bucklin and Gupta (1992), and Siddarth, Bucklin, and Morrison (1995), we created a composite measure of a brand's promotional status. Brand-level promotions were formed by averaging a brand's coupon,[6] feature, display, and temporary price reduction dummy variables. Using a composite measure for promotions offers several advantages over separating the promotion variables. First, our substantive concern lies with the impact of promotions on stockpiling, and according to category managers, all of the promotional activities tend to induce stockpiling.[7] Second, the composite measure substantially reduces the number of parameters to be estimated (by as many as 48 parameters, assuming no cross-parameter correlations), thereby enhancing the parsimony of the model and the reliability of the results. Third, the composite measure reduces the multicollinearity, resulting in more robust estimates (the correlation induced by splitting the promotion variable in our data was substantial; the determinant of the split promotion correlation matrix was .009). This collinearity is due to the tendency of manufacturers to increase their use of different promotional vehicles concurrently over time (*The Marketer* 1990). The remaining variable, household

[5]Prices are in nominal terms. The category average prices in 1992 were only 3% higher than those in the first quarter of 1984.

[6]Coupon availability for a brand was inferred from the coupon redemption information. When redemptions of a brand's coupons exceeded one standard deviation above the mean weekly redemptions for that brand, a coupon was said to be available (Mela, Gupta, and Lehmann 1997). A brand was said to be on feature, display, or temporary price reduction if any of its brand sizes were on promotion.

[7]The possibility that different types of promotions have different long-term effects is discussed in greater detail in the "Managerial Issues" section.

inventory level (INV), was inferred by the procedure outlined by Bucklin and Gupta (1992).

Long-term exposure to promotions. Our measure of long-term exposure to promotions (LTPROM) follows Papatla and Krishnamurthi's (1996). Specifically, we created a geometrically lagged series using the history of households' exposure to promotions on each shopping trip. The measure is also similar to Jacobson and Obermiller's (1990) adaptive model of expectations and therefore suggests that LTPROM also can be interpreted as a household's expectation of a deal arising in the subsequent period. Consequently, long-term exposure to promotions for household i at time t was operationalized as

$$(11)\quad LTPROM_{it} = \lambda LTPROM_{i,t-1} + (1-\lambda)PROM_{i,t-1};$$

$$0 \le \lambda < 1,$$

where $PROM_{i,t-1}$ is the category-level promotion in shopping trip t – 1 and λ is the carryover effect, or lag coefficient, to be estimated. As λ approaches one, all prior promotions are defined to carry equal weight, and the influence of a promotion does not decay over time. Smaller values for the carryover effect attenuate the long-term influence of promotions; as λ approaches zero, promotions offered prior to t – 1 are specified to have negligible influence. Note that the formulation in Equation 11, with the proper error assumptions, is equivalent to the distributed lag or Koyck model. We use the first year of data to initialize the long-term variable, because we have no information on households' exposure to promotions prior to their entering the panel. We use the remaining seven-and-one-quarter years of data to calibrate the model.

Purchase incidence and conditional purchase quantity. Each shopping trip record contains data on whether a purchase was made in the category and the number and size of the units purchased, if applicable. From this information, an indicator variable was created for whether the household made any purchase in the category during the shopping trip. This variable served as our incidence measure. Conditional purchase quantity was obtained from the number of ounces bought by the household.

Model Specification

To assess how a household's price and promotion responses are affected by its long-term exposure to promotions, we first model the incidence utility for the category during a particular shopping trip as a function of price (PRICE), short-term promotion (PROM), and inventory (INV). Mean household purchase rate (PRATE) also was included as a control for cross-household heterogeneity.[8] The utility function for category purchase incidence in Equation 1 is specified as

$$(12)\quad U_{it} = \beta^I_{0it} + \beta^I_{1it}PROM_{it} + \beta^I_{2it}PRICE_{it} + \beta^I_{3it}INV_{it} + \beta^I_4 PRATE_i + \varepsilon^I_{it},$$

where the varying parameters, β^I_{mit}, are reparameterized further as a function of long-term exposure to promotions. That is,

$$(13)\quad \beta^I_{mit} = \gamma^I_{m0} + \gamma^I_{m1}LTPROM_{it} + \nu^I_{mit}.$$

Note that β^I_4 is fixed over time because PRATE is included to capture cross-household heterogeneity.

As in the incidence model, we model conditional purchase quantity as a function of price, short-term promotion, and inventory. To accommodate the possibility that loyals behave differently in their purchase quantity decisions (Krishnamurthi, Mazumdar, and Raj 1992; Krishnamurthi and Raj 1991), we specify the conditional quantity model at the brand level[9] and include loyalty (as in Guadagni and Little 1983)[10] as a control variable.[11] Following Krishnamurthi and Raj (1988), we also include household mean purchase quantity (MQTY) as a control variable for cross-household heterogeneity. The expression for the conditional quantity purchased for brand b therefore is given by

$$(14)\quad Q_{ibt} = \beta^q_{0ibt} + \beta^q_{1it}PROM_{ibt} + \beta^q_{2it}PRICE_{ibt} + \beta^q_{3it}INV_{it} + \beta^q_4 MQTY_i + \beta^q_5 LOY_{ibt} + \sigma^{qI}_{it}W_{it} + \varepsilon^q_{it},$$

where W_{it} is a selectivity bias term that captures the dependency between the incidence and conditional purchase quantity decisions (Maddala 1983, p. 223).[12] We then reparameterize the varying parameters in Equation 14 to capture the effect of a household's long-term exposure to promotions on its current purchase quantity decision,

[8]Time-varying and fixed household purchase rate variables yielded virtually identical results in the incidence model; however, the model fit was slightly decreased for the time-varying purchase rate variable.

[9]Of this category's purchases, 99% are single-brand purchases. Thus, $Q_{it} \approx Q_{ibt}$, and the brand quantity given in Equation 14 also can be interpreted to reflect the category purchase quantity. We are grateful to the editor for noting this congruency, and we use this interpretation in subsequent discussions.

[10]Following Fader, Lattin, and Little (1992), we used a lag of .83 to create the loyalty variable. This lag is also in the middle of the range of values used by Guadagni and Little (1983), Gupta (1988), and Papatla and Krishnamurthi (1996). As in Gupta's (1988) work, results were robust to variations in the lag.

[11]We thank an anonymous *JMR* reviewer for this suggestion and its resulting model specification. We also ran a conditional *category* quantity model (1) without loyalty or brand intercepts and (2) using category level PROM and PRICE in lieu of brand level variables and obtained virtually identical results.

[12]The general expression for W_{it} is given by (the complete derivation is available from the first author)

$$W_{it} = \frac{\phi\left[\dfrac{-\sum_{m=0}^{M}\left(\sum_{j=0}^{J}\gamma^I_{mj}z^I_{ijt}\right)x^I_{mit}}{\sigma^I_{it}}\right]}{\left\{1-\Phi\left[\dfrac{-\sum_{m=0}^{M}\left(\sum_{j=0}^{J}\gamma^I_{mj}z^I_{ijt}\right)x^I_{mit}}{\sigma^I_{it}}\right]\right\}}.$$

Table 1
SUMMARY TABLE OF HYPOTHESES

Hypothesis	*Parameter*	*Expected Sign*
Incidence Hypotheses		
H_1: Main effect of long-term promotions on incidence	γ^I_{01}	Negative
H_2: Long-term effect of promotions on incidence promotion sensitivity	γ^I_{11}	Negative
H_3: Long-term effect of promotions on incidence price sensitivity	γ^I_{21}	Negative[a]
H_4: Long-term effect of promotions on incidence inventory sensitivity	γ^I_{31}	Negative[a]
Quantity Hypotheses		
H_5: Main effect of long-term promotions on quantity	γ^q_{01}	Positive
H_6: Long-term effect of promotions on quantity promotion sensitivity	γ^q_{11}	Positive
H_7: Long-term effect of promotions on quantity price sensitivity	γ^q_{21}	Negative[a]
H_8: Long-term effect of promotions on quantity inventory sensitivity	γ^q_{31}	Negative[a]

[a]A negative long-term effect of promotions on these parameters implies that households become increasingly price and inventory sensitive.

Table 2
VARIABLE MEANS

Variable	*First 4½ Years*	*Second 4½ Years*
Promotion (percent of store visits with promotion)	.085	.141
Price ($/ounce)	.046	.049
Inventory (ounces)	−7.44[a]	12.52
Long-term promotions	.08	.14
Mean expected household quantity[b] (ounces/visit)	1.09	1.08

[a]Inventory is mean centered.
[b]Expected quantity is the product of the incidence likelihood and the conditional purchase quantity. A graph of mean household incidence likelihoods and mean household conditional purchase quantities over time is provided in Figures 1 and 2.

$$(15)\qquad \beta^q_{0ibt} = \gamma^q_{00b} + \gamma^q_{00} + \gamma^q_{01}\ \text{LTPROM}_{it} + v^q_{0it}$$

and

$$\beta^q_{lit} = \gamma^q_{10} + \gamma^q_{11}\ \text{LTPROM}_{it} + v^q_{lit},$$

where γ^q_{001} is set to zero to ensure Equation 15 is identified. β^q_4 and β^q_5 are fixed over time, because MQTY and LOY are control variables included to capture cross-household heterogeneity.

Before discussing the results, it is helpful to restate our hypotheses in terms of our expectations regarding the γ parameters in the incidence and quantity models. In Table 1, we present a summary of our hypotheses regarding the expected signs of these coefficients.

The main effect of long-term promotions is equivalent to the effect of long-term promotions on the intercept in Equations 12 and 14. We standardized all of the independent variables to mean zero and variance one to facilitate comparison of effect sizes.

EMPIRICAL ANALYSIS AND RESULTS

In Table 2, we report the mean values for the key variables (unstandardized) of concern for both the first and second half of the data. Comparing marketing activity in each half of the data provides a concise overview of any potential changes in marketing policy. A clear shift in strategy is evident, as the frequency of promotions has increased notably over the duration of the data.

Figure 1
MEAN LIKELIHOOD OF INCIDENCE AND PROMOTIONAL FREQUENCY OVER TIME

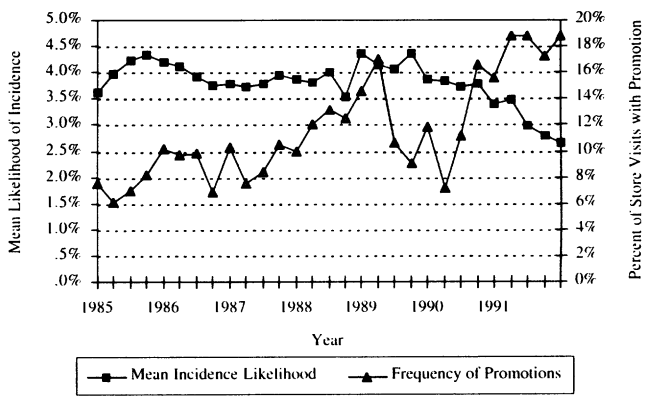
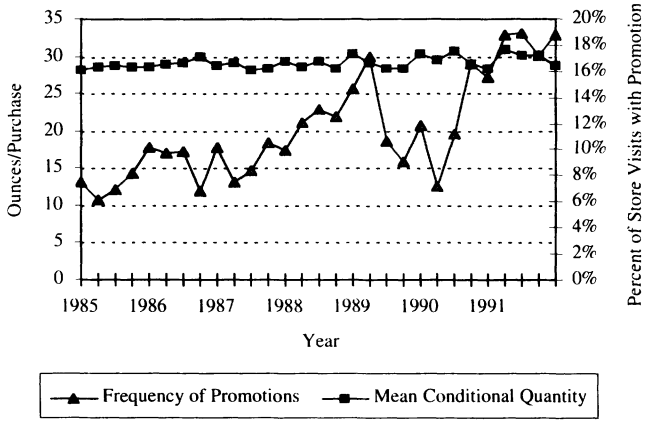


Figure 1 portrays mean promotions (percentage of store visits with a promotion) and mean purchase incidence rates (number of purchases over number of shopping trips) by quarter. A trend regression of the mean quarterly promotion series indicates that promotions have increased significantly over time ($p < .001$). A trend regression of the incidence data suggests that mean quarterly purchase rates across households have diminished over time ($p < .001$). Therefore, promotions have increased over time, whereas the likelihood of purchase incidence has diminished.

Figure 2 graphs mean promotions and mean purchase quantities conditioned on incidence over time. A trend regression of the quantity series suggests that mean quarterly purchase quantities have increased over time ($p < .01$).

Coupled with the decrease in incidence likelihoods, the increase in conditional purchase quantities might be indica-

Figure 2
MEAN CONDITIONAL QUANTITIES AND PROMOTIONAL FREQUENCY OVER TIME



tive of the lying-in-wait heuristic discussed previously. Moreover, in the first half of the data, the mean price paid when a purchase incidence occurred was .03 cents/ounce less than when a purchase was not made. In the latter half of the data, as the frequency of promotions increased, the difference increased sevenfold to .21 cents/ounce. The tendency to seek out lower prices and buy larger purchase quantities offers further evidence of the lying-in-wait heuristic. Also consistent with this heuristic are the larger inventories that households carried in the second half of the data (see Table 2).

Note that households' mean expected purchase quantities (the product of incidence likelihood and conditional quantity) remain constant over time, even though incidence rates and conditional quantities have changed (see Table 2). By analyzing consumers' incidence and conditional quantity decisions separately, we are able to uncover underlying changes obscured by their product (i.e., incidence probabilities decrease whereas conditional quantities increase). The constant level of expected purchase quantities is consistent with a pattern of constant consumption. Increasing expected quantities would be more consistent with a pattern of increased consumption.

Model Selection

We calibrated and compared several alternative incidence and quantity model specifications to assess whether (1) the long-term effect of promoting and (2) the parameter error structure add significantly to the model. Assessing whether long-term effects are significant is one of our core research concerns. The second issue is also important because no stockpiling studies (as opposed to choice; e.g., Gönül and Srinivasan 1993) to our knowledge have tested for the significance of stochastic parameters. In all models tested, we control for selectivity bias (i.e., the correlation between the incidence and conditional quantity decisions). We also allow the varying parameter errors to covary within[13] and across[14] the incidence and quantity equations. Because all the alternative specifications are nested, we use the likelihood ratio test to assess the best-fitting model. In Table 3, we present a more detailed description of the various models tested, as well as their fit.

The results in Table 3 show that both the long-term effects and the parameter error structure contribute significantly to model fit in the incidence and quantity models. Table 3 also indicates that the gain in fit for the incidence model arising from long-term effects is similar to the gain for accommodating parameter error.

Short-Term Effects

In Table 4, we present the estimated coefficients for the best-fitting model (the "short- and long-term effects with parameter errors" model in Table 3). As is expected, increased price significantly decreases both the propensity to purchase and the quantity purchased. The negative short-term effect of price increases on category incidence and purchase quantity (see Table 4) has been well documented in some research, though other studies have found no effect of price on purchase timing or acceleration (Gupta 1991). Promotions have a significant positive effect on incidence and no effect on quantity. The stronger effect of promotion on

[13]We allow parameter errors to covary within the incidence and quantity models, because other researchers have found them to covary (Gönül and Srinivasan 1993).

[14]Parameter error correlations across the incidence and quantity models were constrained to common parameters (e.g., incidence price parameter error with quantity price parameter error). A nested test confirms the suspicion that cross-equation, cross-parameter errors do not improve the model fit significantly.

Table 3
SUMMARY STATISTICS FOR MODEL SELECTION

	Incidence (n = 105,515)			*Quantity[a] (n = 3866)*		
Model[b]	*Degrees of Freedom*	*ln L*	*L. R. Test*	*Degrees of Freedom*	*ln L*	*L. R. Test*
Short-term effects with no parameter errors	5	−16081.3	86.6*	14	−13758.8	259.2*
Short-term effects with parameter errors	11	−16054.1	32.2*	24	−13638.9	19.4*
Short- and long-term effects with no parameter errors	9	−16058.4	40.8*	18	−13749.0	239.6*
Short- and long-term effects with parameter errors	15	−16038.0	—	28	−13629.2	—

*$p < .001$.

[a]Summary statistics for quantity models are conditional on selected incidence model.

[b]The short-term effects models constrain $(\gamma^{l}_{01} \ldots \gamma^{l}_{31} = 0, \gamma^{q}_{01} \ldots \gamma^{q}_{31} = 0)$. The no-parameter-errors models constrain $(v^{l}_{01} \ldots v^{l}_{31} = 0, v^{q}_{01} \ldots v^{q}_{31} = 0, \sigma^{q}_{it} = (\sigma^{q}_{0})^2, \sigma^{l}_{it} = (\sigma^{l}_{0})^2$, and $\sigma^{ql}_{it} = \sigma^{ql}_{00})$.

the incidence decision is similar to Gupta's (1988) and Krishnamurthi and Raj's (1991) studies. Increased inventory significantly reduces purchase incidences. The negative effect of inventory on purchase incidence has been well documented in some research (Bucklin and Gupta 1992; Gupta 1988), whereas other studies have found no effect (Chintagunta 1993). The effect of inventory on purchase quantity is negative and strongly significant. Again, though seemingly intuitive, some studies have found little effect of inventory on purchase quantity (Gupta 1988). Finally, two of the control variables (mean purchase quantity and purchase rate) are strongly significant and correctly signed. The remaining control variable, loyalty, is insignificant. This finding is consistent with Bodapati, Lal, and Padmanabhan's (1997). The strength and consistency of the short-term results help lend validity to our model findings.

Long-Term Effects

Implied duration of promotions. We performed a grid search to obtain the best-fitting value for the lag parameter, λ. The likelihood maximizing estimate for the promotional lag is .96. To assess the duration of the long-term effect of promotions, we calculated the implied 90% duration interval (Clarke 1976) for this value of lag and compared it to studies that assess the long-term effect of promotions on choice. With a decay parameter of .96, the implied 90% duration interval (Clarke 1976) is approximately 56 store visits, or 21 weeks. This result is similar to the duration interval estimated by Mela, Gupta, and Lehmann (1997), who find the 90% decay interval of both long-term promotional and advertising effects on brand choice to be approximately 2.58 quarterly periods, or 33 weeks. Our decay estimate is also similar to, but less than, the advertising decay found in Clarke's (1976) study, of approximately 39 weeks, which suggests that promotions have a slightly less enduring effect.

The long-term impact of promotions on category purchase incidence. H_1 suggests that the main effect of a household's long-term exposure to promotions on its likelihood of purchase incidence is negative. The coefficient for the main effect of long-term promotions is negative and strongly significant (see Table 4).

H_2 suggests that, in the long term, promotions will make households less promotion sensitive, and as is expected, we observe a negative and significant result for the long-term effect of promotions on promotion sensitivity. This result confirms our premise that consumers seem to be more willing to forego promotions, presumably because they expect a better deal to be just around the corner. H_3 argues that pro-

Table 4
MAXIMUM LIKELIHOOD ESTIMATES

Coefficient	*Purchase Incidence (Standard Error)*	*Purchase Quantity (Standard Error)*
Intercept	**−18.69 (.086)****	**30.53 (1.496)****
Price	**−.26 (.081)****	**−1.01 (.186)****
Promotion	**.68 (.080)****	0.00 (.147)
Inventory	**−1.05 (.076)****	**−.74 (.146)****
Loyalty	—	.53 (.453)
Mean Quantity	—	**7.55 (.164)****
Purchase Rate	**1.78 (.074)****	—
Long-Term Promotion		
Main effect	**−.39 (.090)****	**.57 (.156)****
Effect on promotion sensitivity	**−.15 (.071)****	−.02 (.088)
Effect on price sensitivity	**−.12 (.074)***	**−.33 (.189)****
Effect on inventory sensitivity	−.07 (.071)	−.13 (.131)
Parameter Variance		
σ_{price}	.01	4.95
σ_{promo}	1.64	1.11
σ_{inv}	1.47	1.03
Within Model Covariance		
$\sigma_{pricepromo}$	−1.66	−1.42
$\sigma_{priceinv}$	−.55	1.89
$\sigma_{promoinv}$	−.42	.41
Across Model Covariance		
σ_{ql0}	—	−.30
$\sigma_{qlpriceprice}$	—	.11
$\sigma_{qlpromopromo}$	—	0.00
$\sigma_{qlinvinv}$	—	−.03
Log-likelihood	−16038.50	−13629.25
n	105515	3866

Note: All independent variables are standardized to mean zero and variance 1. Bold indicates significant coefficient.
To conserve space, we do not report brand-specific constants in the quantity model.
*$p < .05$ one-tailed test.
**$p < .025$ one-tailed test.

Table 5
SIMULATION RESULTS

	Elasticities		
	Total Effect	*Incidence Effect*	*Quantity Effect*
Increase price 1% short-term effect only	–.64	–.38	–.26
Increase promotions 1% short-term effect only	.12	.12	0.00
Increase promotions 1% long-term effect only	–.12	–.16	.04
Increase promotions 1% total effect	0.00	–.04	.04

motions will make households more price sensitive in the incidence decision, and the result is nearly significant in a one-tailed test. The finding implies that it is becoming increasingly difficult to maintain or raise prices as promotions become more common.

Although the sign of the long-term effect of promotions on inventory sensitivity is as predicted, the relationship is not significant. Therefore, H_4 is not supported.

The long-term impact of promotions on conditional purchase quantity. As is hypothesized in H_5, the long-term effect of promotions on average quantity bought, given a purchase incidence, was significantly positive. This result, combined with the finding that the long-term effect of promotions on purchase incidence is negative, provides further evidence for the lying-in-wait heuristic.

Our speculative hypothesis, H_6, regarding the effect of promotions on promotion sensitivity is not supported. This finding, coupled with the insignificant short-term effect of promotions on quantity, is consistent with Gupta's (1988) finding that promotions play a greater role in the incidence decision than they do in the quantity decision. H_7 is supported, which suggests that households are becoming more price sensitive in the conditional quantity decision as promotions become more common.

Inventory sensitivity increases as promotions become more commonplace, which weakly supports H_8 ($p < .16$). This result indicates that households burdened with large inventories are likely to purchase lower quantities in response to increased long-term exposure to promotions. This result might account, to some degree, for the insignificant result regarding the effect of inventory in studies such as Gupta's (1988). In categories in which promotions are infrequent, inventory might not play a significant role in stockpiling behavior.

Managerial Issues

Assessing long- and short-term incidence and quantity price and promotion elasticities. Our empirical results suggest that promotions have a positive short-term effect on stockpiling. They also indicate that the long-term effect of promotions is negative on incidence and positive on quantity. It is not clear, however, if the short-term gains from promotions outweigh the long-term losses and whether incidence accounts for more of the promotions' effects than quantity. We address these issues by running a simulation to decompose the total impact of a 1% increase in price and promotions into short- and long-term effects and into incidence and quantity effects.

To obtain the price decomposition, we employ the following procedure: Let Q_0 be the simulated purchase quantity using actual data. Let Q_1 be the simulated purchase quantity, given a 1% price increase in the incidence model and no price increase in the conditional quantity model. Let Q_2 be the simulated purchase quantity, given a 1% price increase in both the incidence and purchase quantity models (Guadagni and Little 1983). The total price elasticity, η_t, is $(Q_2 - Q_0)/1$. Similarly, the incidence price elasticity, η_I, is $(Q_1 - Q_0)/1$. The quantity price elasticity is then the difference between the total elasticity and the incidence elasticity, $\eta_t - \eta_I$. We follow the same procedure to decompose promotional response into an incidence and a quantity promotional elasticity. In this simulation, the promotion variable was increased by 1%, and the long-term promotional variable was updated accordingly. The incidence and quantity effects were separated as outlined previously. To partial the short- and long-term effects of promotion, we constrained the long-term promotion variables to be unchanged while increasing the short-term promotional variable by 1%. This simulation enabled us to calculate the short-term effects of promotions on incidence and expected quantity. The long-term effect of promotions then is obtained by taking the difference between the total effect of promotions and the short-term effect of promotions. The results of these simulations are presented in Table 5.

The overall stockpiling price elasticity is –.64, which is lower than Tellis's (1988) meta-analytic mean price elasticity of –1.76. We suspect our lower mean arises from modeling category incidence and quantity price elasticities, as opposed to brand switching elasticities (Gupta 1988), which often are found to be greater in magnitude. Consistent with Gupta's (1988) work, the incidence elasticity (–.38) is greater than the quantity elasticity (–.26).

The estimated short-term promotional elasticity is .12. The low elasticity arises from the relatively modest increase represented by a 1% change in the frequency of promotions. We further observe that the combined long- and short-term elasticity of promotions is zero. In this category, stockpiling induced by promotions in the short term is essentially offset by reduced demand in the long term. In essence, increased sales are more the result of borrowed future sales than increased consumption, and there is no category expansion effect. The long-term effects are consistent with our hypotheses; in response to increasing promotions in the long term, households are buying more product, less often. This result suggests an increased sophistication on the part of households in their ability to buy on promotion (i.e., lying in wait).

Managerial implications. The insights arising from both our simulation and model have several important manageri-

al implications regarding the profitability of promotions.[15] The simulation suggests that, in the long term, promotions do not increase category demand. Because promotions cost a great deal, it seems apparent that promotions reduce category profitability. As a caveat, we note that this observation might not be surprising. In mature product categories, promotions are designed to induce stockpiling and brand switching rather than increase category demand. However, the long-term effect of promotions on primary demand has implications for this competitive game. The finding that promotions do not tend to increase category demand suggests that promotions might lead to more of a prisoner's dilemma problem than was previously suspected.

Our consumer model also explicitly suggests some behavioral mechanisms by which promotions can undermine profitability in the long term. First, promotions increase price sensitivity. The increase constrains category profitability because it becomes more difficult to raise prices. Second, promotions lead to greater inventories, thereby suppressing demand in subsequent, nonpromoted periods. As a result, the likelihood of nonpromoted purchases decreases, which further reduces category profitability. Third, promotions become increasingly less effective, making it necessary to offer more costly promotions in the future. Fourth, the pattern of lying in wait for promotions (buying more, less often) leads to greater volatility in sales. This volatility exacerbates the task of managing inventories, thereby increasing costs and further reducing category profitability. Each of the behavioral changes brought about by promotions has conspired to induce potentially serious, albeit unintended, consequences for managers.

In summary, our analysis has several important ramifications for managers regarding how promotions affect category profitability in the long term. Furthermore, many of the behavioral findings regarding consumer stockpiling provide novel insights into how promotions affect sales. Many of these long-term implications have been theorized widely, yet our analysis is one of the first to offer empirical substantiation of these theories.

Comparing the long-term effects of price and nonprice promotions. An additional issue of managerial interest pertains to whether different types of promotions have different long-term effects on stockpiling. For example, manufacturers might want to know whether price-oriented promotions have a greater tendency to induce consumers' lie-in-wait behavior over the long term. Were price-oriented promotions the primary drivers of such behaviors, managers might want to alter their promotional mix. Because of the near multicollinearity of long-term promotions in our data (determinant of split promotion quantity model regressors = .0006), we were unable to test directly for these differential effects by including price and nonprice promotions in the same model. Consequently, we reestimated our model by redefining promotion as price promotions. We then repeated the analysis by redefining promotions as nonprice promotions. Although subject to variable omission bias, the results of both models were nearly identical to the results of the composite model. Using a paired comparison t-test, we found none of the parameters to be significantly different ($p < .05$) across models. However, as the long-term promotional strategies were too highly correlated in our data to assess confidently how such effects differ, we recommend that manufacturers consider "decoupling" their differing promotional activities in certain test markets to explore more fully whether price and nonprice promotions have differing long-term effects on stockpiling.

[15]We are grateful to an anonymous *JMR* reviewer for motivating this discussion and providing many of these implications.

CONCLUSIONS

Contributions

The goal of this study is to assess the long-term effect of promotions on consumer stockpiling behavior. Such an analysis complements recent research into how increasing promotions have affected consumer brand choice. To analyze how such increases affect stockpiling behavior, we generate several hypotheses regarding how increases in the frequency of promotions affect households' decisions regarding whether and how much to buy. These hypotheses lead us to develop a joint model of purchase incidence and purchase quantity in which households' responsiveness to price and promotion are allowed to vary with changes in households' exposure to promotions over long periods of time. Given the longitudinal nature of the research question, we calibrate this model on an eight-and-one-quarter-year scanner panel.

We hypothesize that households develop price expectations on the basis of their prior exposure to promotions over a long period of time, such as months or years. We argue that these expectations, coupled with the costs of inventorying product, affect consumer purchase timing and purchase quantity decisions. We assert that increasing expectations of future promotions lead to (1) a reduced likelihood of purchase incidence on a given shopping trip and (2) an increase in the quantity bought when a purchase is made. This strategy is consistent with a consumer learning to wait for especially good deals and then stockpiling when those deals occur. Overall, our results are consistent with these hypotheses.

The result that consumers adapt buying strategies has an important analytical implication previously raised by Assunçao and Meyer (1993), Erdem and Keane (1996), and others. Traditional optimization methods use marketing mix response functions to determine optimal pricing and promotion. However, after a policy is developed, the consumers adapt, which possibly leads to new optima. Erdem and Keane (1996) suggest that the failure to accommodate dynamics in behavior leads to bias in the estimates of policy outcomes. By accommodating changing behavior, structural model approaches such as ours take an important step toward enabling estimates of optimal levels of marketing activity.

Finally, we offer several insights regarding the long-term effect of promotions on category profitability. Promotions lead to higher price sensitivities, reduced promotional efficacy, greater inventories, and higher demand volatility. These effects all conspire to hurt category profits. Although many prior studies have theorized such effects, ours is among the first to document them.

Further Research

Our results and analyses suggest several extensions. First, our model is calibrated on one category in one market. As additional data sets with a sufficient history of promotional

activity and purchasing behavior become available, generalizability of our results across categories will become feasible. Second, our theory assumes that households develop a knowledge of prices on the basis of prior exposure to promotional activity. Such an assumption might be reasonable (Krishna 1991), but it could benefit from more thorough testing. Third, long-term exposure to promotions also might affect consumption and purchase rates. Some early short-term work has been done in this area (Ailawadi and Neslin 1998; Assunçao and Meyer 1993; Wansink and Deshpandé 1994) and could benefit from taking a varying parameter approach.

The recent interest in research into the long-term effects of promotions and the opportunities that remain for additional research suggest that this research stream will prove fruitful in years to come. We hope that other studies will continue to use the long streams of scanner panel data that are increasingly available to explore further the longitudinal dimension of consumer behavior. The limited amount of research regarding the long-term effects of marketing activity, when compared to the substantial body of work regarding short-term effects, suggests that such exploration can continue to yield high dividends to researchers and managers.

REFERENCES

Ailawadi, Kusum and Scott A. Neslin (1998), "The Effect of Promotion on Consumption: Buying More and Consuming It Faster," *Journal of Marketing Research,* forthcoming.

Assunçao, Joao L. and Robert J. Meyer (1993), "The Rational Effect of Price Promotions on Sales and Consumption," *Management Science*, 39 (May), 517–35.

Bell, David R. and Randolph E. Bucklin (1996), "Investigating the 'Incidence' of Reference Effects: A Nested Logit Approach with Latent Segments," working paper, Anderson School, UCLA.

Blattberg, Robert C., Richard Briesch, and Edward J. Fox (1995), "How Promotions Work," *Marketing Science*, 14 (3), G122–32.

——— and Scott A. Neslin (1989), "Sales Promotion: The Long and Short of It," *Marketing Letters*, 1 (1), 81–97.

——— and ——— (1990), *Sales Promotion: Concepts, Methods, and Strategies*. Englewood Cliffs, NJ: Prentice Hall.

Bodapati, Anand V., Rajiv Lal, and V. Padmanabhan (1997), "Correlation Between Choice and Quantity Behavior, or, Does Loyalty Matter?" paper presented at 1997 Marketing Science Conference, Berkeley, CA (March).

Boulding, William, Eunkyu Lee, and Richard Staelin (1994), "Mastering the Mix: Do Advertising, Promotion, and Sales Force Activities Lead to Differentiation?" *Journal of Marketing Research*, 31 (May), 159–72.

Bucklin, Randolph E. and Sunil Gupta (1992), "Brand Choice, Purchase Incidence, and Segmentation: An Integrated Modeling Approach," *Journal of Marketing Research,* 29 (May), 201–205.

——— and James M. Lattin (1991), "A Two-State Model of Purchase Incidence and Brand Choice," *Marketing Science*, 10 (1), 24–39.

Clarke, Darral G. (1976), "Econometric Measurement of the Duration of Advertising Effects on Sales," *Journal of Marketing Research*, 13 (November), 345–57.

Chintagunta, Pradeep K. (1993), "Investigating Purchase Incidence, Brand Choice, and Purchase Quantity Decisions of Households," *Marketing Science*, 12 (2), 184–208.

Dekimpe, Marnik G. and Dominique M. Hanssens (1995a), "The Persistence of Marketing Effects on Sales," *Marketing Science*, 14 (1), 1–21.

——— and ——— (1995b), "Empirical Generalizations About Market Evolution and Stationarity," *Marketing Science*, 14 (3), G109–21.

Dillon, William R. and Sunil Gupta (1996), "A Segment-Level Model of Category Volume and Brand Choice," *Marketing Science*, 15 (1), 38–59.

Erdem, Tulin and Michael P. Keane (1996), "Decision-Making Under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets," *Marketing Science*, 15 (1), 1–20.

Fader, Peter S., Bruce G.S. Hardie, John D.C. Little, and Makato Abe (1992), "Market Response with Purchase Feedback," working paper, Wharton School, University of Pennsylvania.

———, James M. Lattin, and John D.C. Little (1992), "Estimating Nonlinear Parameters in the Multinomial Logit Model," *Marketing Science*, 11 (4), 372–85.

Forbes (1991), "The Trend is Not Their Friend," 148 (September), 114–19.

Gönül, Füsun and Kanaan Srinivasan (1996), "Estimating the Impact of Consumer Expectations of Coupons on Purchase Behavior: A Dynamic Structural Model," *Marketing Science*, 15 (3), 262–79.

——— and ——— (1993), "Modeling Multiple Sources of Heterogeneity in Multinomial Logit Models: Methodological and Managerial Issues," *Marketing Science,* 12 (3), 213–3.

Guadagni, Peter M. and John D.C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 2 (3), 203–208.

Gupta, Sunil (1988), "Impact of Sales Promotions on When, What, and How Much to Buy," *Journal of Marketing Research*, 25 (November), 342–56.

——— (1991), "Stochastic Models of Interpurchase Time with Time-Dependent Covariates," *Journal of Marketing Research*, 28 (February), 1–15.

Helsen, Kristiaan and David C. Schmittlein (1992), "Some Characterizations of Stockpiling Behavior Under Uncertainty," *Marketing Letters*, 3 (1), 5–16.

Jacobson, Robert and Carl Obermiller (1990), "The Formation of Expected Future Price: A Reference Price for Forward-Looking Consumers," *Journal of Consumer Research*, 16 (March), 420–32.

Jain, Dipak C. and Naufel J. Vilcassim (1991), "Investigating Household Purchase Timing Decisions: A Conditional Hazard Function Approach," *Marketing Science*, 10 (1), 1–23.

Kalyanaram, Gurumurthy and Russell S. Winer (1995), "Empirical Generalizations from Reference Price Research," *Marketing Science*, 14 (3), G161–69.

Krishna, Aradhna (1991), "The Effect of Dealing Patterns on Consumer Perceptions of Deal Frequency and Willingness to Pay," *Journal of Marketing Research*, 28 (November), 441–51.

——— (1992), "The Normative Impact of Consumer Price Expectations for Multiple Brands on Consumer Purchase Behavior," *Marketing Science*, 11 (3), 266–86.

——— (1994), "The Impact of Dealing Patterns on Purchase Behavior," *Marketing Science*, 13 (4), 351–73.

Krishnamurthi, Lakshman, Tradib Mazumdar, and S.P. Raj (1992), "Asymmetric Response to Price in Consumer Brand Choice and Purchase Quantity Decisions," *Journal of Consumer Research*, 19 (December), 387–400.

——— and S.P. Raj (1988), "A Model of Brand Choice and Purchase Quantity Price Sensitivities," *Marketing Science*, 7 (1), 1–20.

——— and ——— (1991), "An Empirical Analysis of the Relationship between Brand Loyalty and Consumer Price Elasticity," *Marketing Science,* 10 (2), 172–83.

Lal, Rajiv and V. Padmanabhan (1995), "Competitive Response in Equilibria," *Marketing Science*, 14 (3), G101–108.

Lee, Lung-Fei and Robert P. Trost (1978), "Estimation of Some Limited Dependent Variable Models with Applications to Housing Demand," *Journal of Econometrics*, 8, 357–82.

Maddala, G.S. (1983), *Limited Dependent and Qualitative Vari-*

ables in Economics. New York: Cambridge University Press.

——— (1985), "A Survey of the Literature on Selectivity Bias as It Pertains to Health Care Markets," *Advances in Health Economics and Health Services Research*, 6, 3–18.

——— (1991), "A Perspective on the Use of Limited Dependent and Qualitative Variables Models in Accounting Research," *The Accounting Review*, 66 (October), 788–807.

The Marketer (1990), "Trade Promotion Junkies," (October), 30–33.

Mela, Carl F., Sunil Gupta, and Kamel Jedidi (1998), "Assessing Long-Term Promotional Influences on Market Structure," *International Journal of Research in Marketing*, forthcoming.

———, ———, and Donald R. Lehmann (1997), "The Long-Term Impact of Promotion and Advertising on Consumer Brand Choice," *Journal of Marketing Research*, 34 (May), 248–61.

Mela, Richard L. (1965), "Sales Budgeting for Controlled Growth Objectives," *Journal of Marketing Research*, 2 (May), 133–40.

Nelson, Forrest D. (1977), "Censored Regression Models with Unobserved Stochastic Censoring Thresholds," *Journal of Econometrics*, 6 (3), 309–27.

Papatla, Purushottam and Lakshman Krishnamurthi (1996), "Measuring the Dynamic Effects of Promotions on Brand Choice," *Journal of Marketing Research*, 33 (February), 20–35.

Progressive Grocer (1995), "The Prisoner's Dilemma," (May), 99–101.

Siddarth, S., Randolph E. Bucklin, and Donald G. Morrison (1995), "Making the Cut: Modeling and Analyzing Choice Set Restriction in Scanner Panel Data," *Journal of Marketing Research*, 32 (August), 255–67.

Tellis, Gerald J. (1988), "The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales," *Journal of Marketing Research*, 25 (November), 331–41.

The Wall Street Journal (1996), "P&G Bets on Low Prices 'Every Day' To Cut Out Need for Company Coupons," (January 8).

Wansink, Brian and Rohit Deshpandé (1994), "Out of Sight, Out of Mind: Pantry Stockpiling and Brand-Usage Frequency," *Marketing Letters*, 5 (January), 91–100.