

# Managing Advertising and Promotion for Long-Run Profitability

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## Abstract

In recent years, manufacturers have become increasingly disposed toward the use of sales promotions, often at the cost of advertising. Yet the long-term implications of these changes for brand profitability remain unclear. In this paper, we seek to offer insights into this important issue. We consider the questions of i) whether it is more desirable to advertise or promote, ii) whether it is better to use frequent, shallow promotions or infrequent, deep promotions, and iii) how changes in regular prices affect sales relative to increases in price promotions. Additional insights regarding brand equity, the relative magnitude of short- and long-term effects, and the decomposition of advertising and promotion elasticities across choice and quantity decisions are obtained.

To address these points, we develop a heteroscedastic, varying-parameter joint probit choice and regression quantity model. Our approach allows consumers' responses to short-term marketing activities to change in response to changes in marketing actions over the long term. We also accommodate the possibility of competitive reactions to policy changes of a brand. The model is estimated for a consumer packaged good category by using over eight years of panel data. The resulting parameters enable us to assess the

effects of changes in advertising and promotion policies on sales and profits.

Our results show that, in the long term, advertising has a positive effect on "brand equity" while promotions have a negative effect. Furthermore, we find price promotion elasticities to be larger than regular price elasticities in the short term, but smaller than regular price elasticities when long-term effects are considered. Consistent with previous research, we also find that most of the effect of a price cut is manifested in consumers' brand choice decisions in the short term, but when long-term effects are again considered, this result no longer holds. Last, we estimate that the long-term effects of promotions on sales are negative overall, and about two-fifths the magnitude of the positive short-term effects.

Finally, making reasonable cost and margin assumptions, we conduct simulations to assess the relative profit impact of long-term changes in pricing, advertising, or promotion policies. Our results show regular price decreases to have a generally negative effect on the long-term profits of brands, advertising to be profitable for two of the brands, and increases in price promotions to be uniformly unprofitable.

*(Long-Term Effects; Promotions; Advertising; Price Sensitivity; Scanner Data; Choice; Purchase Quantity; Switching Regression)*

## 1. Introduction

In the last few years, Procter and Gamble has been trying to lead the consumer packaged goods industry by reducing trade promotions and coupons (*The Wall Street Journal*, January 15 and January 22, 1997), emphasizing advertising and brand building, and following an EDLP pricing strategy. Two driving factors appear to be at the core of P&G's strategy—cost reduction through better supply chain management (Kurt Salmon Associates 1993), and a belief that, in the long term, advertising is good and promotions are bad for brands. However, a recent survey of manufacturers and retailers shows that many companies in the industry have not followed P&G's lead (Cannondale Associates 1998). In fact, this survey shows that the proportion of marketing budget allocated to trade promotions has grown from 44% in 1997 to 47% in 1998, a trend that continues the increase of the past decade. Companies continued reliance on promotions may stem from the fact that, while it is easier to assess the short-term effects of promotions (a topic that many academic studies have also focused on), it is much harder to determine the long-term effects of promotions and advertising. The task of assessing long-run effects is exacerbated by the fact that competitors often respond to changes in marketing policy. Unless companies can measure, quantify and compare the short- and long-term effects of promotions and advertising on brand sales and profits, it is difficult to imagine how they may arrive at the appropriate budget allocation between these two marketing elements. Although important, this issue is relatively under-researched (Blattberg et al. 1995, Bucklin and Gupta 1998, Gupta 1993).

The purpose of our study is to fill this gap by determining and comparing the *short-* and *long-term* effects<sup>1</sup> of *promotions* and *advertising* on consumers' purchase behavior (including both choice and quantity) and consequently on the long-run profitability of a brand. Accordingly, we develop a model and use eight years of disaggregate data to address this goal. In the process,

<sup>1</sup>Consistent with Fader et al. (1992) we define short-term effects of promotion and advertising as current effects (e.g., the effects of this week's promotions on sales), and long-term effects as those occurring over several quarters or years.

we also broach such tactical questions as i) "is it better to offer frequent shallow discounts or infrequent deep discounts," and ii) "is it better to charge high regular price and offer deep discounts or vice versa?"

### 1.1. Related Research and Contributions of the Paper

A few recent studies have also examined some of the questions that we are addressing in this paper. It is, therefore, appropriate to highlight how our effort differs from and builds upon previous research. The main objective of our paper is to provide substantive insights and an approach to managing advertising and promotion for the long-run profitability of brands while taking into account changes in consumers' and competitors' behavior over time. Specifically, our paper addresses the following issues.

1. *Advertising-Promotion Tradeoff*: We address the strategic issue of how best to allocate resources between advertising and promotion. Using model results and a simulation that accounts for both short- and long-term effects, changes in consumers' behavior, and competitors' reactions, we conclude that it is perhaps unwise for all brands to unilaterally increase advertising and cut promotions or vice versa. In other words, the ad-promotion tradeoff is brand specific. It depends on brand-specific advertising and promotion effects as well as the current level of resources allocated to these two decisions.

In contrast, many recent studies have examined the long-term effects of either advertising or promotion, but not both. Therefore, these studies are unable to offer any insight on the issue of advertising-promotion tradeoff. For example, Dekimpe and Hanssens (1995a, 1995b) include only advertising, while Papatla and Krishnamurthi (1996) and Mela et al. (1998) include only promotions. Studies that incorporated both these decisions also have significant limitations. For example, Boulding et al. (1994), and Mela, Gupta, and Lehmann (1997—hereafter MGL) provided only directional results (i.e., they do not consider whether short-term effects outweigh long-term effects or the relative costs of different strategies) and may have inadvertently left the impression that somehow advertising is "good" and promotions are "bad." Sethuraman and Tellis (1991) examined the trade-off between advertising and price discounting. However, their study has

two major limitations as the authors themselves indicated. First, “. . . our measures are only short-term elasticities. Advertising may have longer term effects . . .” (page 172). Second, “we did not analyze . . . the effect of advertising on price elasticity . . .” (page 172).

2. *Brand Equity*: We capture the main effects of advertising and promotions on consumers’ purchase behavior.<sup>2</sup> Results indicate that advertising has a long-run positive effect on brand choice while the opposite holds for promotions. In a loose sense this confirms managerial intuition that advertising enhances brand equity while promotion hurts it. Note three things. First, many studies (e.g., Mela et al. 1998) focus on category-specific, not brand-specific, issues. Second, while some studies (e.g., Kamakura and Russell 1993) captured the main effects and not the interactions (i.e., the long-run effect of advertising on price sensitivity), others accounted for interactions and not the main effects (e.g., MGL, Papatla, and Krishnamurthi 1996). Third, even if advertising has a positive effect on brand equity, our previous discussion (regarding current expenditure levels) suggests why it may not be appropriate for a brand to continue increasing its advertising.

3. *Competitive Effects*: We explicitly model and account for competitive reactions in assessing the long-run impact of marketing decisions. As expected, inclusion of these reaction functions, in general, lowers the elasticity of price, promotion and advertising. This in turn influences the profit impact of these marketing variables. Inclusion of competitive reactions is also a relatively new aspect of the paper which is absent from studies addressing the long-run issue (e.g., DeKimpe and Hanssens 1995a, Mela, et al. 1998, MGL, Papatla, and Krishnamurthi 1996). If promotions make consumers more price sensitive, then competitors may intensify promotions. These competitive moves may offset each other leaving the market shares unchanged. In this scenario, although consumers have become more price sensitive over time due to increased promotions, we may not see any changes in brand shares. In other words, it is important to go beyond share and

understand changes in consumer and competitor behavior. By explicitly studying these changes, our study provides richer insights for both researchers and managers.

4. *Promotion Depth Versus Frequency*: Is it better to offer infrequent, deep discounts or frequent, shallow discounts? To the best of our knowledge no other study has addressed this tactical issue empirically in the context of long-term effects. We find that depth elasticities are larger than frequency elasticities in the short run but become smaller when long-run effects are considered.

5. *Regular Price Versus Promotion*: Is it better for a brand to raise its regular price and offer price promotions or is the brand better off offering lower regular price with limited price promotions? Our paper provides an approach to address this issue. For our data set we find that, for three of the four brands analyzed, it is better to raise prices and lower promotions (i.e., these brands have been hurting their profits on both price and promotion dimensions), while, for the other brand, it is better to lower price and lower promotions. Once again, this issue has not been addressed in previous studies.

6. *Long- and Short-Run Tradeoffs*: Our paper allows us to explicitly capture the short- and long-run tradeoffs. For example, we find that, on average, long-term effects of promotions (depth and frequency) are about two-fifths of the short-term effects. Due to modeling and technical limitations, previous papers assessing the long-term effect of promotions and advertising on choice (e.g., MGL) could *not* provide this tradeoff.

7. *Impact on Choice and Quantity Decisions*: In addition to brand choice, our paper explicitly captures the effects of marketing policies on purchase quantity. This builds on previous studies such as MGL, Mela et al. (1998) and Papatla and Krishnamurthi (1996). Our results show that while choice accounts for a large proportion of the total promotion elasticity in the short run (consistent with Bucklin et al. 1998 and Gupta 1988), quantity accounts for the majority of this elasticity when both short- and long-run effects are considered. Further, we find that these effects vary significantly by brands. Finally, we also decompose the advertising effects on choice and quantity. Although a number of researchers have decomposed the effects of

<sup>2</sup>Our analysis captures the long term effect of promotions and advertising on brand intercepts which have been interpreted as a measure of brand equity (Kamakura and Russell 1993).

promotions across behaviors (cf. Bucklin et al. 1998, Gupta 1988), ours is the first to conduct a similar analysis for advertising.

8. *Methodology*: Finally, the paper provides a methodological contribution by developing a varying parameter multinomial probit and regression model with selectivity bias. This model is new to both the marketing and econometric literature.

In sum, this study provides significant insights about managing advertising and promotion for long-run profitability of brands—insights that were not available from previous studies.

The rest of the paper is organized as follows. In § 2 we describe our model. Section 3 discusses estimation issues. Section 4 describes the data and § 5 presents the results. In § 6, we use these results to conduct simulations and draw managerial implications about the long-term value of promotions and advertising. Section 7 presents conclusions and offers directions for future research.

## 2. Model

A consumer's decision of which brand to buy and how much quantity of that brand to buy depends on brand-specific factors (e.g., price and promotion of various brands) and consumer-specific factors (e.g., consumer's brand loyalty, consumption rate, product inventory, and his/her sensitivity to price and promotion). Further, long-term marketing activities of brands may alter consumers' sensitivity to short-term marketing actions. For example, extensive advertising over the years may make consumers less sensitive to short-term price discounts. Conversely, frequent discounting by a brand may make consumers more price sensitive. This suggests that consumers' sensitivities to short-term marketing activities can vary over time as a function of long-term marketing actions. Conceptually this is similar to the varying-parameter regression models developed in econometrics (see Johnston 1984, pp. 407–419 for a discussion). Our modeling approach may be summarized as follows:

- Consumer's choice of brand  $j$  at time  $t = f(\beta_{jt}^c X_{jt}^c) + \epsilon_{jt}^c$
- Consumer's quantity decision given choice of brand  $j$  at time  $t = g(\beta_{jt}^q X_{jt}^q) + \epsilon_{jt}^q$

- Choice parameters  $\beta_{jt}^c = h_c(\gamma_j^c Z_{jt}^c) + e_{jt}^c$
- Quantity parameters  $\beta_{jt}^q = h_q(\gamma_j^q Z_{jt}^q) + e_{jt}^q$

where  $X_{jt}^c$  are the short-term marketing variables affecting brand choice (such as weekly price and promotion),  $X_{jt}^q$  are the short-term variables affecting purchase quantity (some of these could be the same variables that affect choice, such as price), and  $Z_{jt}^c$  and  $Z_{jt}^q$  are long-term marketing variables (e.g., advertising) and consumer-specific factors (e.g., brand loyalty).

We would like our model to accommodate three key characteristics. First, the parameters  $\beta_{jt}^c$  and  $\beta_{jt}^q$  should vary over time and be allowed to change with changes in long-term marketing strategy of a brand. However, long-term variables do not capture all the changes in these parameters. The error terms  $e_{jt}^c$  and  $e_{jt}^q$  are specifically included to capture this aspect. This would make the choice and quantity models heteroscedastic. Second, the model should allow the error terms in the choice and quantity models to be correlated due to omitted variables which affect both these decisions (Dubin and McFadden 1984). Previous studies (e.g., Lee and Trost 1978, Lee 1982, Krishnamurthi and Raj 1988) show that ignoring this correlation can lead to biased parameter estimates. Finally, the error terms in the choice model should be correlated across brands to avoid the IIA assumption.

To capture these key features, we use a heteroscedastic probit model for brand choice and a heteroscedastic regression model which controls for selectivity bias for the quantity model (e.g., Lee and Trost 1978).<sup>3</sup> Selectivity bias refers to the bias in parameter estimates that results from ignoring the dependence between the choice and quantity models. The models are estimated using a maximum likelihood approach. Conceptually this is a straightforward extension of the approach used by Lee and Trost (1978) and Krishnamurthi and Raj (1988). However, as we will discuss shortly, the

<sup>3</sup>Strictly speaking, regression models assume quantity to be continuous, when in fact, quantity for many packaged goods (such as the one we analyze) is actually discrete. However, the specification of a continuous quantity model has little practical effect on our results and greatly simplifies model estimation. Specifically, in our application, we found the correlation between parameters estimated from regression and parameters estimated from an ordered logit to be 0.97. In addition, predicted expected quantities from each model were within 1% while estimated elasticities differed less than 0.03%.

details of the model derivation and estimation are quite different from the previous approaches.

Following the discrete choice modeling stream, we assume that consumers choose a brand to maximize their brand choice utility. Specifically, the utility of brand  $j$  for consumer  $i$  at purchase occasion  $t$  is given by

$$U_{ijt} = \sum_k \beta_{ijk}^c X_{ijk}^c + \epsilon_{ijt}^c \quad (1)$$

where  $X_{ij0t}^c = 1$ ,  $\beta_{ij0t}^c$  is brand  $j$ 's choice intercept,  $X_{ijk}^c$  ( $k = 1, \dots, K$ ) is the  $k$ th short-term marketing variable affecting consumer  $i$ 's brand choice behavior (e.g., price of a brand in a certain week), and  $\beta_{ijk}^c$  is the associated parameter reflecting consumers' sensitivities to the short-term marketing activity.

Given the choice of a brand  $j$ , the consumer proceeds to buy a certain quantity of that brand. Following Krishnamurthi and Raj (1988), a simple regression model may be used to capture this behavior. Specifically, the quantity of brand  $j$  bought by consumer  $i$  at time  $t$  is given by

$$Q_{ijt} = \sum_l \beta_{ijlt}^q X_{ijlt}^q + \epsilon_{ijt}^q \quad (2)$$

where  $X_{ij0t}^q = 1$ ,  $\beta_{ij0t}^q$  is brand  $j$ 's quantity intercept, and  $X_{ijlt}^q$  ( $l = 1, \dots, L$ ) is the  $l$ th short-term marketing variable affecting consumer  $i$ 's decision of how much quantity of brand  $j$  to buy. As indicated earlier, the error terms  $\epsilon_{ijt}^c$  and  $\epsilon_{ijt}^q$  could be correlated due to omitted variables which may affect a consumer's decision of both which brand to buy and how much quantity of that brand to buy.

Next we allow the short-term sensitivities (including the intercepts  $\beta_{ij0t}^c$  and  $\beta_{ij0t}^q$ ) to be affected by a brand's long-term marketing actions. This effect is captured as follows:

$$\beta_{ijk}^c = \gamma_{jk0}^c + \sum_m \gamma_{jkm}^c Z_{ijmt}^c + e_{ijkt}^c \quad (3)$$

$$\beta_{ijlt}^q = \gamma_{jl0}^q + \sum_m \gamma_{jlm}^q Z_{ijmt}^q + e_{ijlt}^q \quad (4)$$

where  $\gamma_{jkm}^c$  and  $\gamma_{jlm}^q$  are moderating parameters.

Assuming the errors in Equations (1)–(4) to be normally distributed, the likelihood function can be derived as shown in Appendix A.

### 3. Estimation

To obtain estimates for the quantity and choice parameters, we can maximize the joint likelihood function  $LL$  in Equation (A-10). Although this is possible, such a procedure can be very cumbersome (see Maddala 1983, p. 224). Following Lee (1982), Lee and Trost (1978), and Krishnamurthi and Raj (1988), we develop a consistent two-stage maximum likelihood procedure for estimating our model. To formulate this procedure, we need to obtain the conditional expectation and the conditional variance of  $Q_{ijt}$  given choice of brand  $j$ . These conditional moments for brand  $j = 1$  are derived in Appendix B.

Given the normality assumption, the conditional likelihood function for brand  $j$ 's quantity data is:

$$L_j = \prod_t \prod_{Q_{ijt} > 0} \frac{1}{\phi_{ijt}} \phi \left( \frac{Q_{ijt} - \tau_{ijt}}{\phi_{ijt}} \right) \quad (5)$$

where  $\phi(\cdot)$  is the standard normal density function,  $\tau_{ijt}$  is the conditional mean and  $\phi_{ijt}^2$  is the conditional variance (see Appendix B, Equations (B-1) and (B-4)). Note that  $L_j$  depends on both the choice and quantity parameters.

It is now straightforward to develop a two-stage estimation procedure. We first develop a varying-parameter maximum likelihood probit method to estimate the choice parameter vector  $\Theta^c$  by  $\hat{\Theta}^c$  using all of the observations. We then use  $\hat{\Theta}^c$  to calculate  $\hat{W}_{ijt}(\cdot)$  and  $\hat{V}_{ijt}(\cdot)$  for all  $i, j, t$  (see Appendix B). Next we maximize  $\log L_j$ ,  $j = 1 \dots J$  given the estimated values  $\hat{W}_{ijt}(\cdot)$  and  $\hat{V}_{ijt}(\cdot)$  to obtain estimates for the selectivity bias parameters  $\sigma_j^{qc}$  and the quantity model parameters.

The parameter estimates produced by the two-stage procedure are consistent (Heckman 1979, Lee 1982). However, the standard errors of the estimates may not be exact since the choice parameters are computed independently of the quantity parameters and because the second stage estimation ignores the fact that  $W_{ijt}$  and  $V_{ijt}$ ,  $j = 1 \dots J$  are estimated. Ideally, we should maximize  $LL$  in Eq. (A-10) to get asymptotically efficient estimates and correct standard errors for both the choice and the quantity model parameters  $\Theta = (\Theta^c, \Theta^q)$ . As mentioned above, this is very difficult because of the high nonlinearity of the likelihood function (Maddala 1983, Lee and Trost 1978). Alternatively, as

suggested by Lee and Trost (1978, p. 368) and Krishnamurthi and Raj (1988), we adopt a two-step maximum likelihood (2SML) estimation which utilizes the Newton-Raphson method to maximize  $LL$  in only one iteration using the consistent estimates as starting values. The asymptotic covariance matrix is consistently estimated by the inverse of the hessian (see Krishnamurthi and Raj 1988, p. 7 for details). Because the initial parameter values are consistent, the 2SML estimates have the same asymptotic properties as those of the single step MLE.

Several features distinguish our estimation approach from that of Krishnamurthi and Raj (1988). First, because of the normality assumption and the error in parameters, we use a varying-parameter multinomial probit method instead of a logit to estimate the choice parameters. Second, for the same reason, we use a varying-parameter ML regression instead of OLS to estimate the quantity and the selectivity bias parameters. Unlike OLS, ML regression explicitly accounts for the heteroscedasticity of the error terms and simultaneously estimates all of the variance components of the quantity model.

## 4. Data

### 4.1. Descriptives

We used IRI scanner data for a nonfood, mature product category. The data are comprised of panel, store, demographic, and trip data. The data were collected in a medium sized Midwestern market. The panel is a static panel (no households enter or exit) and consists of 1,590 households observed over an eight and one quarter year period running from 1984 to 1992. The demographics of the static panel do not deviate substantially from the national averages. Households' median and mean interpurchase times are 6 and 12 weeks respectively. In addition, no brand entries or exits occurred over the data period. As a result, product-life cycle and product introduction factors are not likely to impact our analysis.

The large quantity of data (both observations and brands) makes model estimation virtually intractable. We therefore randomly sampled about half of the households. Additionally, we confined our analysis to the four largest brands which comprise 71% of the

market share in this category (our selection procedure is similar to Krishnamurthi and Raj (1988) who chose three brands comprising 80% share). Households who did not buy any of these four brands, and observations in which households did not purchase one of the four brands were eliminated from the analysis. This left us with 691 households who made 13,664 purchases. There are four brand-sizes in our data. The medium two sizes account for over 75% of all purchases, and switching between all sizes is common. The model is estimated at the brand rather than the brand-size level for several reasons. First, we account for size in our quantity analysis. Second, the large number of brand size alternatives makes model estimation considerably more difficult. Third, management believes most marketing actions are intended to promote the brand rather than a specific brand-size. Fourth, this approach is consistent with many previous studies (e.g., Papatla and Krishnamurthi 1996). Basic descriptives for the data are given in Table 1.

### 4.2. Variables

**Choice Model Specification.** We begin by specifying a utility function that outlines how consumers respond to price changes in the short-term, and then specify a model of how consumers adapt their responses to changes in advertising and price promotion policies over time. Specifically, utility of brand  $j$  for consumer  $i$  at time  $t$  is defined as<sup>4</sup>

$$U_{ijt} = \beta_{ij0t}^c + \beta_{ij1t}^c \text{PRICE}_{jt} + \beta_{ij2t}^c \text{PROM}_{jt} + \epsilon_{ijt}^c \quad (6)$$

where the intercept, price (PRICE) and price promotion (PROM) sensitivity parameters are further reparameterized as functions of long-term advertising (LTADV), long-term promotion (LTPROM), and brand loyalty (LOY) as follows:

$$\beta_{ijkt}^c = \gamma_{jk0}^c + \gamma_{k1}^c \text{LTADV}_{jt} + \gamma_{k2}^c \text{LTPROM}_{jt} + \gamma_{k3}^c \text{LOY}_{ijt} + e_{ijkt}^c. \quad (7)$$

Note we are suggesting that advertising and promotion policies may affect choice (and subsequently profits) in two ways: via a direct effect on brand choice probabilities (changing intercepts) and via an indirect effect on a household's response to price and promotions (changing sensitivities).

<sup>4</sup>Details of variable operationalization are given in the next section.

Several theories support the existence of a direct effect of advertising and promotions on consumers' choice. For example, self perception theory suggests that consumers who buy on promotions are likely to attribute their behavior to the presence of promotions and not to their personal preference of the brand (Dodson et al. 1978). Frequent use of promotion is therefore likely to reduce consumers' intrinsic preference for the brand, i.e., it may hurt "brand equity" (Kamakura and Russell 1993). In contrast, advertising is likely to strengthen brand image and build equity (Aaker 1991). The main effect of loyalty simply controls for heterogeneity in consumer preferences for different brands (Guadagni and Little 1983).

There is also significant theoretical support for the indirect effect of advertising and promotions on consumers' choice. Economic theory suggests that advertising leads to product differentiation which reduces consumers' price sensitivity (Comanor and Wilson 1974). Kaul and Wittink (1995) provide an excellent summary of marketing studies which also conclude similar interaction effect of advertising on price sensitivity. Increased use of price promotions, on the other hand, is likely to reduce product differentiation and therefore increase consumers' price sensitivity (Boulding et al. 1994). These effects are expected to be moderated by consumers' loyalty to brands. In other words, loyal consumers (almost by definition) are likely to be less price sensitive than nonloyal consumers. The interaction of loyalty with price and promotion sensitivities captures this effect.

**Operationalization of Choice Model Variables.** The price (PRICE) of a selected brand is the regular (nonpromoted) price per ounce. For each brand, price is operationalized as the lowest price per ounce across that brand's different sizes. As consumers commonly switch across brand sizes in this category, the minimum price across brand-sizes reflects the lowest price available to a given household for the nonselected brand. The minimum price operationalization is better than weighted averages at capturing brand-level price variance in categories where size switching is common.

Price promotion (PROM) reflects the discount offered by the brand. Blattberg et al. (1995) outline evidence that promotional price elasticities may exceed

**Table 1** Descriptive Statistics of the Data

Variable	Brand	Mean for 1984-1987	Mean for 1988-1991
Market Share	1	0.35	0.36
	2	0.11	0.13
	3	0.16	0.13
	4	0.10	0.12
Purchase Quantity per Occasion (oz)	1	27.72	28.41
	2	26.20	28.58
	3	28.04	30.27
	4	28.60	29.42
Regular Price per Ounce (\$)	1	0.051	0.054
	2	0.050	0.055
	3	0.052	0.056
	4	0.048	0.053
Promotion Frequency (% of occasions)	1	15.4	33.4
	2	8.7	32.6
	3	10.2	25.3
	4	6.4	29.8
Promotion Depth (% off)	1	11.3	17.9
	2	12.1	17.3
	3	13.8	16.8
	4	29.8	20.2
Advertising <sup>1</sup> (\$)	1	66.61	29.78
	2	25.52	17.55
	3	45.26	26.70
	4	28.98	12.25

<sup>1</sup>Advertising represents average inflation-adjusted advertising dollars in thousands spent in a quarter.

regular price elasticities. The PROM variable enables us to accommodate this possibility. Moreover, the PROM variable contains information about the presence of (i.e., frequency) and the magnitude of (i.e., depth) price promotions thereby enabling us to disentangle the effects of frequency and depth on brand sales and profitability. As with price, we use a maximum discount formulation (analogous to minimum price) for nonselected brand sizes.

Loyalty (LOY) is defined as a household's share of purchases of a brand over the last four non-promoted purchases. The four period purchase cycle represents approximately 48 weeks of purchases and is the duration used in MGL. We used only nonpromoted purchases to avoid influencing the loyalty measure with promotional purchase events (Lattin 1990).

To assess the impact of long-term promotional or

advertising activity of a brand on consumers' price and promotion sensitivities, we defined these long-term variables as a geometric series of past promotional and advertising activities. Specifically,

$$\begin{aligned} \text{LTADV}_{jt} = & \text{ADV}_{jt} + \lambda \text{ADV}_{j,t-1} \\ & + \lambda^2 \text{ADV}_{j,t-2} + \lambda^3 \text{ADV}_{j,t-3} + \dots, \end{aligned} \quad (8)$$

and

$$\begin{aligned} \text{LTPROM}_{jt} = & \text{PROM}_{jt} + \lambda \text{PROM}_{j,t-1} \\ & + \lambda^2 \text{PROM}_{j,t-2} + \lambda^3 \text{PROM}_{j,t-3} + \dots. \end{aligned} \quad (9)$$

This formulation is consistent with the Koyck model specification which has been extensively used in the literature to study the carryover effects of advertising (Clarke 1976, Leone 1995). Using *quarterly* data, Clarke (1976) estimated the decay parameter ( $\lambda$ ) of advertising to be 0.6. Since price and promotion vary on a *weekly* basis, our unit of analysis is a week. Accordingly, we chose a decay factor of 0.97 for each week,<sup>5</sup> which is equivalent to a decay close to 0.6 after one quarter.<sup>6</sup>

Quarterly, inflation-adjusted advertising expenditures were furnished by the advertising agency of the firm that supplied us the data. Since our unit of analysis is a week, we created an approximation of weekly advertising spending (ADV) by dividing the quarterly advertising by 13 weeks. Once the weekly advertising variable and decay parameters are defined, the long-term advertising variable (LTADV) for any week  $t$  is obtained using Equation (8). This procedure implicitly assumes advertising to be constant over the thirteen weeks in a quarter. However, since our focus is on assessing the long-term (not weekly) impact of advertising, some deviations from this assumption should not

<sup>5</sup>To test the stability of our results across differing values of the decay parameters, we also estimated our choice model using  $\lambda$  values of 0.7, 0.8, 0.9. All of the coefficients and most of the standard deviations were very stable for the various lags. Model fit was best with a lag of 0.97.

<sup>6</sup>This decay or lag value is between those reported by Papatla and Krishnamurthi (1996) for an average quarterly purchase cycle (0.84) and the mean quarterly lag (0.44) in MGL. MGL also find that the lag values for advertising and promotion were not significantly different.

affect our results significantly.<sup>7</sup> Using the decay parameter and the mean weekly price promotion activity of a brand across stores, we similarly obtained the long-term promotion variable (LTPROM) from Equation (9).

**Quantity Model Specification and Variable Operationalization.** The quantity of brand  $j$  that consumer  $i$  buys at time  $t$  is specified as

$$\begin{aligned} Q_{ijt} = & \beta_{j0t}^q + \beta_{j1t}^q \text{PRICE}_{jt} + \beta_{j2t}^q \text{PROM}_{jt} \\ & + \beta_{j3t}^q \text{INV}_{it} + \beta_{j4t}^q \text{MQTY}_i + \epsilon_{ijt}^q. \end{aligned} \quad (10)$$

Price (PRICE) and (PROM) have the same operationalization as in the choice model. Households observing a price for their brand choice also face the same price when deciding how much to buy. Inventory (INV) of a household was included to capture the impact of stockpiling in previous purchase occasions on future purchase quantity decisions. Inventory was computed and then mean-centered as in Bucklin and Gupta (1992). Specifically,

$$\text{INV}_{it} = \text{INV}_{i,t-1} + Q_{i,t-1} - \text{CR}_i * I_{i,t-1} \quad (11)$$

where  $Q_{i,t-1}$  is the quantity bought by household  $i$  on store visit  $t - 1$ ,  $I_{i,t-1}$  is the interval of time between store visit  $t - 1$  and  $t$  and  $\text{CR}_i$  is the average weekly consumption rate for household  $i$ . Mean quantity (MQTY) purchased by a household was included to control for heterogeneity in households' buying patterns. This variable was defined as the total amount (in ounces) of the product bought by a household over the entire duration of the data divided by the total number of its purchases over the same period.

Consistent with the choice model, the intercept and sensitivity parameters are specified to vary as a function of long-term advertising, long-term promotion and loyalty as follows:

$$\begin{aligned} \beta_{ijt}^q = & \gamma_{j0}^q + \gamma_{j1}^q \text{LTADV}_{jt} + \gamma_{j2}^q \text{LTPROM}_{jt} \\ & + \gamma_{j3}^q \text{LOY}_{ijt} + \epsilon_{ijt}^q. \end{aligned} \quad (12)$$

<sup>7</sup>We acknowledge that it would be better to use actual weekly advertising data. However, data limitations preclude us from using it (note single source data did not exist in 1984). Given that previous studies have shown negligible short-term effects of advertising (e.g., Tellis 1988), our approximation does not appear to be a serious limitation.



Finally, all independent variables (in both the choice and the quantity models) were standardized to mean zero and unit variance. This was done to facilitate the comparison of effect sizes. Interaction effects (e.g., between advertising and price) were then created by calculating the product of these standardized variables.

## 5. Results

### 5.1. Choice Model

**Short-Term Effects.** Table 2 shows that three of the four regular price terms are significant and all are correctly signed. The market leader, brand 1, has the lowest regular price sensitivity. All four promotion terms are positive and significant. These results are consistent with a large number of studies which show significant short-term effects of price and promotions on consumers' brand choice behavior (e.g., Guadagni and Little 1983, Gupta 1988). Finally, the covariance matrix for the errors show the non-IIA structure across brands.

**Long-Term Effects.** Of greater interest are the long-term effects of promotions and advertising. Table 2 shows that both promotions and advertising have a significant long-term impact on brand intercepts, i.e., they have a significant *main* effect on consumers' brand choice utility. Recall that the intercept in the brand choice model represents the base probability of purchasing a brand controlling for price and promotional activity. Therefore, the brand intercepts capture "the additional utility not explained by measured attributes" and have been used as measures of brand equity by several researchers (Kamakura and Russell 1993). Other researchers have suggested that the equity captured by the intercept term is but one component of brand equity (Swait et al. 1993). Both views imply changes in the brand intercepts contribute to the overall equity of the brand.<sup>8</sup>

In this vein, one would expect advertising to increase brand equity due to the positive brand messages

<sup>8</sup>There is some controversy about whether the intercept in these models really captures brand equity. However, we will use the term brand equity somewhat loosely to indicate an increase in base choice probability.

**Table 2 Results of Model Estimation**

Variables	Choice Model		Quantity Model	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Intercept				
Brand 1	0 <sup>1</sup>		0 <sup>1</sup>	
Brand 2	<b>-7.555<sup>a</sup></b>	0.162	-0.594	1.319
Brand 3	<b>-6.840</b>	0.158	-0.181	0.963
Brand 4	<b>-8.933</b>	0.173	-0.244	2.019
Price				
Brand 1	-0.103	0.130	<b>-1.727</b>	0.153
Brand 2	<b>-2.276</b>	0.166	-0.106	0.476
Brand 3	<b>-0.882</b>	0.154	-0.462	0.307
Brand 4	<b>-0.428</b>	0.179	<b>-1.618</b>	0.367
Price Promotion				
Brand 1	<b>1.172</b>	0.123	<b>0.288</b>	0.148
Brand 2	<b>0.960</b>	0.152	-0.076	0.272
Brand 3	<b>0.818</b>	0.143	0.338	0.278
Brand 4	<b>1.255</b>	0.175	<b>-0.965</b>	0.340
Main Effect				
Long-Term				
Advertising	<b>0.455</b>	0.100	0.018	0.090
Long-Term				
Promotion	<b>-0.405</b>	0.175	<b>0.503</b>	0.122
Loyalty	<b>5.849</b>	0.063	-0.057	0.700
Brand 1 Std. Dev. <sup>2</sup>	5.000 <sup>1</sup>		8.365	
Brand 2 Std. Dev.	6.876		7.760	
Brand 3 Std. Dev.	5.251		8.263	
Brand 4 Std. Dev.	8.181		7.739	
Moderators of Price Sensitivity (Interaction Effect)				
Long-Term				
Advertising	-0.088	0.094	-0.057	0.098
Long-Term				
Promotion	<b>-0.400</b>	0.100	-0.060	0.088
Loyalty	-0.075	0.073	0.079	0.111
Brand 1 Std. Dev.	0.001		2.510	
Brand 2 Std. Dev.	0.131		2.898	
Brand 3 Std. Dev.	0.835		0.020	
Brand 4 Std. Dev.	0.001		4.305	
Moderators of Price Promotion Sensitivity (Interaction Effect)				
Long-Term				
Advertising	0.100	0.090	0.106	0.099
Long-Term				
Promotion	<b>-0.137</b>	0.066	<b>0.170</b>	0.075
Loyalty	-0.075	0.073	0.079	0.111
Brand 1 Std. Dev.	1.142		1.921	
Brand 2 Std. Dev.	0.549		1.109	
Brand 3 Std. Dev.	0.619		1.509	
Brand 4 Std. Dev.	0.001		1.752	

**Table 2 (Continued) Results of Model Estimation**

Variables	Choice Model		Quantity Model	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Selectivity Bias				
Brand 1			-1.541	0.960
Brand 2			-0.184	1.258
Brand 3			-1.131	1.022
Brand 4			-0.251	1.907
Avg. Purchase			<b>6.266</b>	0.076
Quantity				
Inventory			<b>-0.269</b>	0.080
Covariance Matrix for Errors				
	Brand 1	Brand 2	Brand 3	
Brand 2	-0.024			
Brand 3	-1.487	1.791		
Brand 4	1.964	-2.095	-0.368	
Log-likelihood	-8118.00		-49053.46	

<sup>1</sup>Fixed for identification purposes.

<sup>2</sup>Standard deviation of the error in a brand's intercept or response parameter.

<sup>3</sup>Significant parameters are highlighted in **bold**.

often embodied in national brand advertising. Consistent with this expectation we find that the advertising effect is positive and significant. Many theories suggest that, over the long-term, price promotions are likely to reduce brand equity (Blattberg and Neslin 1989, 1990). Consistent with this view, our results show a negative and significant main effect of long-term promotion on consumers' brand choice utility. In sum, it seems that increased price promotions and reduced advertising have a negative main effect on brands' value and choice.

Economic theory as well as previous studies suggest that advertising reduces consumers' price sensitivity. However, for our data set, this effect was not significant. The interaction of long-term advertising with promotion was also insignificant.

Table 2 shows that long-term promotions make consumers more sensitive to changes in regular price but less sensitive to promotional discounts. Frequent promotions may increase consumers' sensitivity to regular price by lowering their reference price (Kalyanaraman

and Winer 1995). For example, frequent promotions of Coke may lower consumers' reference price of Coke from \$1.49 to \$0.99. This would suggest that while a regular price of \$1.49 may be acceptable to consumers in year 1, the same regular price may seem too high in year 4. Frequent promotions (say 50 cents off) are also likely to increase the reference discount level over time. This would imply that while a 50 cents discount may be considered a significant "gain" in year 1, it may not be considered a gain in year 4. This will reduce consumers' sensitivity to promotional discounts over time. In other words, consumers will need an even higher discount to react positively to a brand.

## 5.2. Quantity Model

**Short-Term Effects.** Only two of the price sensitivity terms in the quantity model are significant. It is interesting to note that brands 1 and 4 have the two smallest price parameters in choice, but they have the two largest price parameters in quantity. This suggests that while regular price cuts of brands 2 and 3 lead consumers to switch to these brands, such price changes by brands 1 and 4 make consumers buy more. An aggregate sales elasticity (e.g., DeKimpe and Hanssens 1995b) or a focus on only brand choice (e.g., Papatla and Krishnamurthi 1996) would not be able to uncover this interesting phenomenon. In § 6 we will expand on the managerial implications of these results.

Brand 1's price promotion parameter is positive and significant, suggesting that its deals increase the quantity bought. Contrary to expectation, the effect of brand 4's price promotion on quantity bought is negative and significant. Inspection of the data reveals that brand 4's price deals are nearly exclusively for smaller sizes leading to this unexpected result. The selectivity bias terms are insignificant for all four brands suggesting that, after controlling for the observed variables, the choice and quantity decisions are largely independent in this category. As expected, mean quantity purchased has a positive and significant effect while household inventory has a negative and significant effect on households' purchase quantity decisions.

**Long-Term Effects.** While the main effect of advertising is insignificant, the main effect of long-term

promotions (captured through the intercept) is positive. This suggests that in response to repeated exposure to promotions, consumers learn to lie in wait for especially good deals and then stockpile when they see them (Mela et al. 1998). Further, consistent with this lie in wait heuristic is the finding that the long-term effect of promotions on promotion sensitivity is also positive.

Note that long-term promotions make consumers less promotion sensitive in choice but more promotion sensitive in quantity. This suggests that frequent promotions of brands makes it unnecessary for consumers to switch brands (as it becomes increasingly likely that a deal on the favored brand will be forthcoming) but makes them more likely to stockpile when their favorite brand is on promotion (because they fulfill a greater portion of their demand in promoted periods). For example, if Pepsi is on promotion this week and a consumer prefers Coke, s/he does not have to switch to Pepsi since this consumer expects Coke to be on promotion soon (perhaps next week). When Coke offers a promotion, this consumer is likely to stock up on his/her favorite brand.

## 6. Managerial Implications

Our previous discussion highlights the directional effects of advertising and promotions in the long-term. However, it still leaves our key research questions unresolved. Specifically, we would like our results to help us address the following important questions:

- Do the negative long-term effects of promotions offset their positive short-term effects?
- What are the relative effects of advertising and promotions on choice and quantity?
- What are the managerial implications of these results for resource allocation across advertising and promotions?
- Is it better to lower regular price or to promote more often? The problem is illustrated by a major policy shift by Post cereals in 1996. Post reduced their discounting level and cut their regular prices by twenty percent. This sparked other manufacturers to follow Post's move.
- Given a fixed budget, is it better to offer frequent, shallow or infrequent, deep discounts?

In addition to an understanding of consumer behavior (modeled earlier), answers to these questions require i) an understanding of how competitors will react to these changes in policy, ii) a simulation of how these policy changes and ensuing competitive reactions affect consumers, and iii) a comparison of the incremental response to the incremental cost of these policy changes. In this section, we address each of these three steps, respectively.

### 6.1. Competitive Reaction Functions

Before assessing the impact of changes in a brand's marketing activity, it is important to consider the potential competitive responses they may induce. For example, simulating the effect of an increase in discounts in the absence of competitive reaction could lead to an optimistic assessment of the effects of discounts. If competitors respond to those discounts (a very likely scenario), the efficacy of these discounts may be diminished significantly. Following Leeflang and Wittink (1992, 1996), we estimated the following competitive reaction functions on first differences using OLS.<sup>9</sup>

$$\Delta \text{PRICE}_{jt} = \sum_{j' \neq j} \theta_{1j'} \Delta \text{PRICE}_{j't} + \sum_{j' \neq j} \theta_{2j'} \Delta \text{PROM}_{j't} + e_{1jt} \quad (13)$$

$$\Delta \text{PROM}_{jt} = \sum_{j' \neq j} \theta_{3j'} \Delta \text{PRICE}_{j't} + \sum_{j' \neq j} \theta_{4j'} \Delta \text{PROM}_{j't} + e_{2jt} \quad (14)$$

$$\Delta \text{ADV}_{jt} = \sum_{j' \neq j} \theta_{5j'} \Delta \text{ADV}_{j't} + e_{3jt} \quad (15)$$

where  $\Delta \text{PRICE}_{jt} = \text{PRICE}_{jt} - \text{PRICE}_{j,t-1}$  represents the changes in price over time. First differences for promotion and advertising are defined similarly.

In this formulation, we did not specify advertising reactions in the pricing/promotion equations and pricing/promotion reactions in the advertising equations for two key reasons. First, advertising effects are measured at the quarterly level, while pricing/promotion effects are weekly. Second, they represent conceptually

<sup>9</sup>Inclusion of lagged competitive activity did not significantly improve fit.

distinct marketing practices. For example, it seems much less likely that a price war will spark an advertising response than a price response.

The results of this analysis are presented in Table 3. The results show a high level of competitive reactivity between brands 1 and 3. A decrease in the price of brand 3 results in lower regular prices and higher discounts for brand 1. Further, in response to an increase in the promotional activity of brand 3, brand 1 reduces

its price and increases its promotional activity. Finally, a reduction in the advertising of brand 3 leads to a reduction in the advertising of brand 1. Brand 1 has a similar effect on brand 3. Brands 2 and 4 do not react to changes in price and promotions. However, these brands show competitive reactions in their advertising.

### 6.2. Market Response Simulations: Procedure

To evaluate the effects of changes in marketing policy on brand sales and profits, we conducted a market

**Table 3** Competitive Reactions—Parameter Estimates and (Standard Errors)

A. Price and Promotion Reactions								
Effect on	Effect of							
	$\Delta P_1$	$\Delta P_2$	$\Delta P_3$	$\Delta P_4$	$\Delta PR_1$	$\Delta PR_2$	$\Delta PR_3$	$\Delta PR_4$
$\Delta P_1$	—	0.035	<b>0.085</b>	0.001	—	<b>0.072</b>	<b>-0.205</b>	0.023
	—	(0.027)	(0.026)	(0.021)	—	(0.036)	(0.035)	(0.034)
$\Delta P_2$	0.012	—	0.034	0.006	0.022	—	-0.023	0.019
	(0.013)	—	(0.018)	(0.015)	(0.021)	—	(0.024)	(0.024)
$\Delta P_3$	<b>0.043</b>	-0.031	—	0.012	<b>-0.140</b>	0.010	—	-0.019
	(0.013)	(0.019)	—	(0.015)	(0.021)	(0.025)	—	(0.024)
$\Delta P_4$	0.004	0.009	0.011	—	0.037	0.022	-0.007	—
	(0.016)	(0.024)	(0.023)	—	(0.027)	(0.032)	(0.031)	—
$\Delta PR_1$	—	0.007	<b>-0.068</b>	0.017	—	-0.023	<b>0.212</b>	-0.000
	—	(0.016)	(0.016)	(0.013)	—	(0.022)	(0.021)	(0.021)
$\Delta PR_2$	0.013	—	0.016	0.009	-0.013	—	0.013	0.017
	(0.009)	—	(0.014)	(0.011)	(0.016)	—	(0.018)	(0.018)
$\Delta PR_3$	<b>-0.039</b>	-0.003	—	-0.009	<b>0.165</b>	0.006	—	-0.024
	(0.010)	(0.014)	—	(0.011)	(0.016)	(0.019)	—	(0.018)
$\Delta PR_4$	0.006	0.015	0.003	—	-0.004	0.020	-0.020	—
	(0.010)	(0.015)	(0.014)	—	(0.017)	(0.020)	(0.019)	—
B. Advertising Reactions								
Effect on	Effect of							
	$\Delta AD_1$	$\Delta AD_2$	$\Delta AD_3$	$\Delta AD_4$				
$\Delta AD_1$	—	0.186	<b>0.507</b>	-0.225				
	—	(0.394)	(0.150)	(0.234)				
$\Delta AD_2$	0.044	—	-0.142	<b>0.269</b>				
	(0.093)	—	(0.083)	(0.103)				
$\Delta AD_3$	<b>0.586</b>	-0.694	—	0.333				
	(0.174)	(0.404)	—	(0.247)				
$\Delta AD_4$	0.148	<b>0.746</b>	0.189	—				
	(0.153)	(0.287)	(0.140)	—				

1. *P* refers to PRICE, and *PR* refers to PROM.
2. Significant parameters are highlighted in **bold**.
3. Intercepts are not reported to conserve space.

simulation. The simulations proceeded by first calculating expected shares and purchase quantities in the absence of any changes in marketing policy. This calculation yielded base sales estimates against which the effects of changes in policy can be judged.

**Calculating Base Level Choice Probabilities and Quantity.** Using the parameter estimates from the choice and quantity models and the actual purchase history of each household, we estimated the *base choice probability* and the *base quantity* (conditional on brand choice) for each brand, household and purchase occasion. The expected quantity for each brand was then computed by multiplying the choice probability by quantity conditioned on choice and summing across all occasions for all households.

**Price and Advertising Elasticities.** To assess the impact of a regular price change by a brand, we reduced the price of the target brand by 1%, and adjusted the regular prices and promotions of the other brands by using the competitive response functions reported in Table 3. Choice probabilities for the target brand were then recomputed using the manipulated prices. The new choice probabilities multiplied with the brand's base quantity (i.e., calculated without a price cut) yielded an estimate of the choice elasticities. A similar simulation was performed where price was reduced in both the choice and quantity models, thus yielding the combined price elasticity. Subtracting the first (choice) elasticity from the second (total) provided the quantity elasticity. To assess the effect of advertising on choice and quantity we followed the same procedure.

**Price Promotion Elasticities.** While price appears only as a short-term variable, and advertising only appears as a long-term variable in our model, price promotion appears both as a short- and long-term variable. Therefore, we need to separate the impact of price promotion on choice and quantity, both in the short- and the long-term. This was done as follows. We increased price promotions by 1%. This meant (a) updating the short-term promotion variable by increasing either the frequency or depth of promotions, and (b) updating the long-term promotion variable as per equation (9). Using the updated long-term

promotion variable, we computed the intercepts and the response parameters as per our model. These were then used to estimate the choice probabilities and conditional quantities. Comparing these results with the baseline estimates, we obtained the total (short- plus long-term) effect of promotions on choice and quantity (choice and quantity effects were separated following the procedure used for price and advertising). Next, we increased the short-term promotions by 1%, but kept the long-term promotion variables at their original values. The simulation was repeated to assess the short-term impact of promotion on choice and quantity. The difference between the total and the short-term effect gave us an estimate of the long-term effect of promotions. In each simulation, we assumed competitors reacted as indicated in Table 3.

Note that the forgoing procedure relies on an increase in either the frequency or depth of promotions. To increase the frequency of promotions by 1%, we randomly selected nonpromoted weeks and inserted the incremental promotions (using the brand's mean level of discount) into those nonpromoted weeks. For example, if a brand offered an average 20% discount 10% of the time (over 1000 weeks this would imply 100 price promotions), a 1% increase in the frequency of price promotions would imply a promotion frequency of 10.1% (101 discounts over 1000 weeks). The incremental 0.1% (one) discount would be randomly distributed across the remaining 90% of the nonpromoted weeks (900 in this example) and its discount level would be 20%. In the same scenario, an increase in the depth of price promotions would be simulated by increasing each discount by 1% (in this example, to an average of 20.2%). By simulating both frequency and depth, we can ascertain whether or not an increase in price promotional frequency is preferable to an increase in the discount level.

### 6.3. Simulation Results

**Price Elasticity.** Simulation results are given in Table 4. Three key findings emerge from this table. First, the total price elasticity for the four brands ranges from  $-0.37$  to  $-1.43$  with an average of  $-0.79$ . Second, decomposition of the total price elasticity into choice and quantity components shows that, on average, choice accounts for about 75% while quantity accounts for

**Table 4 Price, Advertising and Promotion Elasticities—Simulation Results**

	Brand Choice	Purchase Quantity	Total
<b>Price Elasticity</b>			
Brand 1	-0.029	-0.337	-0.366
Brand 2	-1.439	0.005	-1.434
Brand 3	-0.558	-0.066	-0.624
Brand 4	-0.338	-0.380	-0.718
<b>Advertising Elasticity</b>			
Brand 1	0.079	0.000	0.079
Brand 2	0.123	0.004	0.127
Brand 3	0.040	0.002	0.042
Brand 4	0.071	0.001	0.072
<b>Promotion Frequency Elasticity</b>			
Brand 1:			
Short-term	0.0132	0.0018	0.0150
Long-term	-0.0156	0.0212	0.0056
Total	-0.0024	0.0230	0.0206
Brand 2:			
Short-term	0.0380	-0.0024	0.0356
Long-term	-0.0426	0.0292	-0.0134
Total	-0.0046	0.0268	0.0222
Brand 3:			
Short-term	0.0186	0.0032	0.0218
Long-term	-0.0146	0.0184	0.0038
Total	0.0040	0.0216	0.0256
Brand 4:			
Short-term	0.0526	0.0060	0.0586
Long-term	-0.0332	0.0018	-0.0314
Total	0.0194	0.0078	0.0272
<b>Promotion Depth Elasticity</b>			
Brand 1:			
Short-term	0.0242	0.0030	0.0272
Long-term	-0.0304	0.0152	-0.0152
Total	-0.0062	0.0182	0.0120
Brand 2:			
Short-term	0.0326	-0.0020	0.0306
Long-term	-0.0578	0.0244	-0.0334
Total	-0.0252	0.0224	-0.0028
Brand 3:			
Short-term	0.0400	0.0034	0.0434
Long-term	-0.0448	0.0306	-0.0142
Total	-0.0048	0.0340	0.0292
Brand 4:			
Short-term	0.0726	-0.0158	0.0568
Long-term	-0.0504	0.0214	-0.0290
Total	0.0222	0.0056	0.0278

about 25% of the total elasticity. Our result that price changes have about three times the impact on consumers' brand switching behavior relative to their purchase quantity behavior is quite similar to the findings of Bucklin et al. (1998). Third, our results extend this finding further by suggesting significant differences across brands. The market leader in this category has a lower choice elasticity than quantity elasticity suggesting its price changes have less impact on consumers' brand switching (because a large number of consumers buy this brand) but more impact on their quantity decisions.

**Advertising Elasticity.** The results in Table 4 show that advertising elasticities vary from 0.04 to 0.13 with an average of 0.08. This average is similar to the advertising elasticity for mature products of 0.05 estimated by Lodish et al. (1995a) and 0.15 by Assmus et al. (1984). Consistent with prior literature we found price elasticities to be significantly larger (almost ten times) than the advertising elasticities. Further, our results show that almost all of the advertising effect is on consumers' choice decision. Presumably, this is due to the brand building nature of the national advertising.

**Promotion Elasticities.** Table 4 yields a number of findings about the effects of increasing the frequency and depth of promotions. First, the total frequency elasticity (choice and quantity, as well as short- and long-term) of promotion ranges from 0.0206 to 0.0272 with an average of 0.0239. The corresponding depth elasticity ranges from nearly 0 to 0.0292 with an average of 0.0165. While these elasticities may appear small relative to regular price elasticities, it is important to note a 1% change in the frequency (or depth) of promotions has a much smaller effect on the average price charged than a 1% change in the regular price. The decrease in a brand's expected price arising from a 1% increase in promotional frequency is given by  $(0.01 \times \text{frequency}) \times \text{depth}$ . Using the average depth (16.8%) and frequency (21.6%) across brands, this implies a 1% increase in frequency (or depth) is tantamount to a 0.036% cut in the regular price. Thus, an equivalent 1% discount in price (in the form of increased frequency) yields a total (total = long-term + short-term) elasticity of  $0.0239/0.036 = 0.67$ , slightly

lower than the regular price elasticity. Similarly, a 1% increase in the depth of promotions yields a total elasticity of 0.46.

Second, while the long-term effects of promotion depth are consistently negative for all brands, these effects are mixed for promotion frequency. On average (across brands), the long-term elasticities of promotional depth are negative and about 58% of their short-term positive effects, and the long-term elasticities of promotional frequency are negative and about 27% of their positive short-term effects. Put differently, the negative long-term effects are nearly two-fifths the positive short-term effects.

Third, compared to price and promotional frequency, depth has the greatest overall short-term effect, but has the lowest overall total effect. Table 5 compares the average price elasticity across brands with the average "equivalized" (on a 1% price change basis) total and short-term frequency and depth elasticities.

This table highlights that deep promotions, by virtue of their vividness, generate a very high response. However, this effect is reversed when long-term effects are also considered. As indicated earlier, in the long-run consumers come to expect discounts and show lower sensitivity to these promotions. It is also possible that consumers begin to believe, in the long-run, that deeper discounts indicate lower quality. Mela and Urbany (1996) find evidence of such attributions in consumer protocols.

Fourth, on average, the price and short-term promotion elasticities in Table 5 are over 9–14 times higher than advertising elasticities. This significantly higher short-term response to promotion compared to advertising may explain the increasing budget allocated to promotions in recent years.

Fifth, Table 4 shows that almost 90% of the positive short-term effects of promotions is accounted for by brand choice. In other words, short-term promotions

have a substantially larger impact on making consumers switch brands rather than making them buy more quantity. This is also consistent with the finding of Gupta (1988). However, when long-term effects are considered, the finding is reversed (the total elasticity is greater for quantity). This is because i) the deleterious long-term effects of promotions on brand equity reduce the effects on choice and ii) the training of consumers to stockpile when they observe an especially good deal increases the effects on quantity.

In sum, promotions have a substantial impact on consumers' purchases with the negative long-term effects being about two-fifths of the positive short-term effects. Moreover, the negative long-term effects appear greater for increased depth of promotions than they do for increased frequency. This highlights a key benefit of our modeling approach, i.e., going beyond directional results to assessing the relative effect sizes and separating the short- and long-term effects.

#### 6.4. The Long-Term Impact of Price Decreases, Advertising and Promotions on Brand Profits

Our previous discussion suggests that advertising has a small effect on brand sales compared to price or promotions. However, these results do not necessarily suggest that firms should advertise less, reduce price, or promote more frequently. The profitability of these various strategies clearly depends upon costs, market response, and current expenditure levels. Using model results and reasonable assumptions made in consultation with the management of the sponsoring company, we arrived at rough estimates of the long-term profit impact of competing marketing activities.

Table 6 outlines our procedure, assumptions, and results. In this table, we calculate base profits by multiplying brands' market level sales by gross margins and then subtracting advertising and promotional expenses. Next, to assess the effect of a 5% price cut on brands' profitability we use the estimated price elasticities to calculate increases in brands' sales. We then recalculate the lower gross margins, multiply the sales by the margins, and subtract advertising and promotion expenses. The percent change from the base profit is then calculated. We proceed similarly for advertising and promotions by using elasticities to calculate

**Table 5 Price and Promotion Elasticities Compared**

	Short-term	Total (Long-Term + Short-Term)
Regular Price	0.79	0.79
Discount Frequency	0.91	0.67
Discount Depth	1.10	0.46

**Table 6 Long-term Impact of Changes in Price, Promotion and Advertising on Profits**

	Brand 1	Brand 2	Brand 3	Brand 4
<b>Base Profits</b>				
Retail Price/oz (\$)	0.052	0.052	0.054	0.050
Manufacturer Price/oz <sup>1</sup> (\$)	0.045	0.045	0.047	0.043
Manufacturer Profit/oz <sup>2</sup> (\$)	0.032	0.032	0.033	0.030
Ounces Sold <sup>3</sup>	17,684,333	6,160,000	7,032,667	5,287,333
Gross Margin (\$)	559,748	194,977	231,161	160,919
Regional Advertising (\$)	1,542,400	689,280	1,151,360	659,840
Market Advertising <sup>4</sup> (\$)	46,272	20,678	34,541	19,795
Market Price Promotion <sup>5</sup> (\$)	42,939	14,957	17,773	12,344
Base Profit (\$)	470,536	159,342	178,887	128,779
<b>Profit Impact of Price Changes</b>				
Price Elasticity	-0.37	-1.43	-0.62	-0.72
Ounces Sold with 5% Retail Price Cut	18,007,956	6,601,672	7,252,086	5,477,148
Gross Margin (\$)	541,491	198,509	226,454	158,361
Profit with 5% Retail Price Cut (\$)	452,280	162,874	174,181	126,221
% Change in Profit	<b>-3.88*</b>	<b>2.22</b>	<b>-2.63</b>	<b>-1.99</b>
<b>Profit Impact of Advertising Changes</b>				
Advertising Elasticity	0.08	0.13	0.04	0.07
Ounces Sold with 5% Advertising Increase	17,754,186	6,199,116	7,047,436	5,306,367
Profit with 5% Advertising Increase (\$)	470,434	159,546	177,646	128,369
% Change in Profit	<b>-0.02</b>	<b>0.13</b>	<b>-0.69*</b>	<b>-0.32*</b>
<b>Profit Impact of Promotion Frequency Changes</b>				
Frequency Elasticity	0.02	0.02	0.03	0.03
Ounces Sold with 5% Frequency Increase	17,702,548	6,166,838	7,041,669	5,294,524
Gross Margin (\$)	560,324	195,194	231,457	161,138
Profit with 5% Frequency Increase (\$)	468,966	158,811	178,296	128,381
% Change in Profit	<b>-0.33*</b>	<b>-0.33*</b>	<b>-0.33*</b>	<b>-0.31*</b>
<b>Profit Impact of Promotion Depth Changes</b>				
Depth Elasticity	0.01	0.00	0.03	0.03
Ounces Sold with 5% Depth Increase	17,694,944	6,159,138	7,042,935	5,294,682
Gross Margin (\$)	560,083	194,950	231,498	161,143
Profit with 5% Frequency Increase (\$)	468,725	158,567	178,338	128,386
% Change in Profit	<b>-0.38*</b>	<b>-0.49*</b>	<b>-0.31*</b>	<b>-0.31*</b>

\*Significant at 0.05 level.

<sup>1</sup>Assume 20% markup (Dhar and Hoch 1996).

<sup>2</sup>Assume 30% variable costs.

<sup>3</sup>Store data projected to all outlets.

<sup>4</sup>Market population is 3% of the region population. Therefore, 3% of regional advertising budget is allocated to the market area under consideration.

<sup>5</sup>Inferred from average frequency and depth and 20% markup.

changes in demand, and subtracting the increased advertising and promotion expenses from revenues in order to obtain brands' profits. Approximate standard errors for profits were calculated using the delta method.

**The Effect of Regular Price Changes on Profits.** As indicated by Table 6, decreases in regular price are not generally profitable in this category. Brands 1, 3, and 4 are at a disadvantage with an additional 5% price decrease, while brand 2 is better off.



In other words, although price decreases can significantly increase sales and revenues, they also have a significant negative impact on margins leaving the overall profits lower.

**The Effect of Advertising Changes on Profits.** A 5% increase in advertising has a very small impact on profits (relative to price) for most brands. Lodish et al. (1995a, b) suggest that, in general, advertising has a very small effect for mature categories, and changes in advertising expenditure have a much smaller effect than changes in advertising copy and quality. Our results are consistent with this finding. Brand 1's mean advertising level is nearly optimal as the advertising profit elasticity is near zero. However, the most recent quarters in the data indicate brand 1's spending has fallen substantially below that mean indicating that brand 1 should consider increasing its advertising again. Brand 2 also stands to benefit from increased advertising. However, brands three and four should reduce their advertising spending levels. In particular, brand 3 should reduce its advertising the most. It has spent nearly double the amount of brands with similar sales suggesting that this prescription to cut advertising may well be reasonable.

**The Effect of Price Promotion Changes on Profits.** A 5% increase in promotions (frequency or depth) significantly affects brand profits from  $-0.31\%$  to  $-0.49\%$ . Like regular price cuts, increasing the frequency or depth of promotions has a negative, albeit small, impact on profits. While comparing the profit impact due to price or promotion changes, it is important to recall that a 1% increase in frequency or depth of promotion is equivalent to an average of 0.036% cut in price.

In sum, we find that, in our product category, decreasing price would generally not be profitable (the exception is brand 2), increasing advertising would have mixed effects on profitability and increased promotions would have a deleterious impact on profits.<sup>10</sup>

#### 6.5. Limitations and Contributions of the Simulation

We recognize that our simulations have limitations. First, our profit estimates are based on assumptions

<sup>10</sup>The small effects of marketing instruments on profits suggest that although the market may not be in perfect equilibrium, it is not far from optimality.

about costs, margins, and retailer pass-through. We have attempted to make these assumptions as reasonable as possible with the help of the sponsoring company's management. However, the results could change for different sets of assumptions. For example, if the cost of promotions is higher than our assumption (e.g., due to lower pass-through by the retailer), then promotions may be even less profitable than they appear in Table 6. Second, the realities of the marketplace also impose some constraints on the actual execution of certain marketing strategies. For example, our results suggest that firms should increase regular price and reduce the level of price promotions. However, in practice, it may not be feasible to increase price without also offering price discounts to obtain retailer support. Furthermore, our analysis focuses almost entirely on manufacturers' perspective. The retailers' motivation may be quite different, making it difficult to execute some of the intended strategies. Finally, our results are based on a single category in a single market.

Nonetheless, we believe our model is a simple and powerful approach that enables researchers to replicate and generalize the results across products and markets. Indeed, this is one of the main contributions of this manuscript. It is the first paper, to our knowledge, that develops marketing budget recommendations predicated upon short- and long-term effects as well as competitive reactions. In the process, the paper develops an integrated methodology consisting of three phases—model, simulation of consumer and competitive response, and profit impact of policy changes. Previous research has typically stopped after the first phase. In contrast, the underlying approach developed herein enables managers to answer important marketing questions such as i) whether or not to increase advertising and decrease promotions, ii) whether to increase or decrease the frequency or depth of promotions, and iii) whether it is better to change regular prices or price promotion levels.

## 7. Conclusions

Substantively, this paper seeks to provide a means to answer several questions regarding the long-term impact of promotions and advertising on brand choice and purchase quantity. Specifically, we examined the

impact of promotions and advertising on “brand equity”; the effects of competitive reactivity; whether promotion’s short-term positive effects outweigh its possible long-term deleterious effects; how the long-term responses to advertising and promotion differ across choice and quantity decisions; the relative effects of advertising, price and promotions on profits; the relative efficacy of the frequency and depth of promotions; and a comparison of the tactics of decreasing regular price with the alternative of increasing discounts.

To address these issues, we developed a new model and an estimation approach that allows for (a) varying parameters to capture changes in consumers’ response to short-term marketing activities due to changes in long-term marketing actions of brands, (b) correlation between errors in brand choice and purchase quantity decisions to avoid selectivity bias, and (c) correlation among brands to avoid the IIA assumption. This leads to a heteroscedastic, varying-parameter probit and regression model which also controls for selectivity bias. We then estimated our model using over eight years of scanner panel data for 691 households for a consumer packaged good.

Our results show that, in the long-term, advertising has a positive and significant effect on “brand equity” while promotions have a negative effect. Although we did not find a significant effect of advertising on consumers’ price sensitivity, we did find that in the long-term, promotions make consumers more price sensitive and less discount sensitive in their brand choice decision. These results suggest that, in the long-term, promotions make it more difficult to increase regular prices and increasingly greater discounts need to be offered to have the same effect on consumers’ choice.

To move beyond the directional results, we conducted several simulations to assess the relative effects of various marketing activities and also to separate these effects into short- versus long-term, as well as the effects on consumers’ brand choice versus purchase quantity decisions. Our results show that, on average, short-term price promotion elasticities (on an equivalent 1% price basis) are about 1.00 compared to regular price elasticities of 0.79. Conversely, total (long- plus short-term) promotion elasticities (0.56) are about 30% lower than regular price elasticities. Both price and

price promotion elasticities are larger than advertising elasticities (0.07). Furthermore, the long-term effects of promotions are negative and are about two-fifths the positive short-term effects. Consistent with Gupta (1988), we found that most of the effect of price, advertising and short-term promotion was on consumers’ brand choice decision. However, in the long-term, the effect of promotions on quantity may be greater than that of choice.

Finally, to assess the relative profit impact of long-term changes in price, advertising, and promotions, we performed additional simulations by making reasonable assumptions about costs and margins. Results show increases in advertising and decreases in price would have mixed effects on brand profitability across the brands while further increasing promotions would have a uniformly negative impact on long-term profits. The results also show that promotional frequency increases are generally less deleterious than promotional depth increases (although the result varies by brand).

There remain several important areas for future research. We would like to reiterate the need to make these results generalizable. A formal dynamic optimization could further yield important insights. Although we model brand choice and purchase quantity, purchase incidence and the effects of marketing activity on purchase timing could further affect the long-term profitability of advertising and promotions. It would be desirable to assess these effects in future studies. Retailer behavior may also be affected by long-term marketing activity and it will be helpful to incorporate this aspect in the model as well. Finally, it would be desirable to develop approaches to simplify the application of the techniques outlined in this paper. This could facilitate their implementation in managerial settings.<sup>11</sup>

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Appendix A

Likelihood Function

We assume the errors in Equations (1)–(4) to be normally distributed as follows:

$$\begin{bmatrix} \epsilon_{ijt}^c \\ \vdots \\ \epsilon_{ijt}^c \end{bmatrix} \sim N(\mathbf{0}, \Sigma^c) = N\left(\begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{11}^c & \sigma_{12}^c & \cdots & \sigma_{1J}^c \\ \vdots & \ddots & & \vdots \\ \sigma_{J1}^c & \sigma_{J2}^c & \cdots & \sigma_{JJ}^c \end{pmatrix}\right), \quad (A-1)$$

$$\begin{bmatrix} \epsilon_{ijt}^q \\ \epsilon_{ijt}^q \end{bmatrix} \sim N(\mathbf{0}, \Sigma^{qc}) = N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{ij}^q & \sigma_{ij}^{qc} \\ \sigma_{ij}^{qc} & \sigma_{ij}^c \end{pmatrix}\right), \quad (A-2)$$

$$e_{ijkt}^c \sim N(0, \theta_{jk}^2), \quad (A-3)$$

$$e_{ijlt}^q \sim N(0, \delta_{jl}^2). \quad (A-4)$$

Several important features of the error structure should be noted. First, the choice errors are normally distributed and are correlated across brands. This gives us a multinomial probit model of brand choice. Second, the errors in the choice and quantity models are correlated as suggested by Lee and Trost (1978) and Krishnamurthi and Raj (1988). Third, both the choice and quantity models have heteroscedastic errors. This is evident if we rewrite the reduced form of Equations (1), (2), (3) and (4) as follows:

$$U_{ijt} = \mu_{ijt}^c + \zeta_{ijt}^c, \quad (A-5)$$

$$Q_{ijt} = \mu_{ijt}^q + \zeta_{ijt}^q, \quad (A-6)$$

where

$$\mu_{ijt}^c = \sum_k (\gamma_{jk0}^c + \sum_m \gamma_{jkm}^c Z_{ijmt}^c) X_{ijkt}^c,$$

$$\mu_{ijlt}^q = \sum_l (\gamma_{jl0}^q + \sum_m \gamma_{jlm}^q Z_{ijmt}^q) X_{ijlt}^q,$$

$$\zeta_{ijt}^c = \sum_k e_{ijkt}^c X_{ijkt}^c + \epsilon_{ijt}^c,$$

$$\zeta_{ijlt}^q = \sum_l e_{ijlt}^q X_{ijlt}^q + \epsilon_{ijlt}^q,$$

and

$$E(\zeta_{ijt}^c) = 0,$$

$$E(\zeta_{ijlt}^q) = 0,$$

$$\text{Var}(\zeta_{ijt}^c) = \sum_k \theta_{jk}^2 (X_{ijkt}^c)^2 + \sigma_{ij}^c = \psi_{ij}^c,$$

$$\text{Var}(\zeta_{ijlt}^q) = \sum_l \delta_{jl}^2 (X_{ijlt}^q)^2 + \sigma_{ij}^q = \psi_{ij}^q,$$

$$\text{Cov}(\zeta_{ijlt}^c, \zeta_{ij't}^c) = \sigma_{ij'}^c,$$

$$\text{Cov}(\zeta_{ijlt}^c, \zeta_{ij't}^q) = \sigma_{ij'}^{qc}.$$

Note that the intercept error variances  $\theta_{j0}^2$  and  $\delta_{j0}^2$  are not estimable and are absorbed in  $\sigma_{ij}^c$  and  $\sigma_{ij}^q$  respectively.

When consumer  $i$  chooses brand  $j$ ,

$$U_{ijt} > U_{idt} \text{ or } \zeta_{ijt}^c - \zeta_{idt}^c > \mu_{idt}^c - \mu_{ijt}^c, \quad (A-7)$$

$$\forall d = 1, \dots, J \text{ and } d \neq j,$$

and

$$Q_{ijt} = \mu_{ijt}^q + \zeta_{ijt}^q. \quad (A-8)$$

Without loss of generality assume that brand  $j$  is brand 1. Then for  $J = 4$  brands,<sup>12</sup> the likelihood of this purchase is (Maddala 1983, p. 63)

$$L_{i1t} = \int_{\mu_{i2t}^c - \mu_{i1t}^c}^{\infty} \int_{\mu_{i3t}^c - \mu_{i1t}^c}^{\infty} \int_{\mu_{i4t}^c - \mu_{i1t}^c}^{\infty} f(\zeta_{i1t}^q, v_{i12t}, v_{i13t}, v_{i14t}) dv_{i12t} dv_{i13t} dv_{i14t} \quad (A-9)$$

where  $v_{ijdt} = \zeta_{ijdt}^c - \zeta_{idt}^c$  and  $f(\cdot)$  is the joint density function of  $(\zeta_{i1t}^q, v_{i12t}, v_{i13t}, v_{i14t})'$  which is multivariate normal with null vector as the mean and the following covariance matrix:

$$\Psi_{i1t} = \begin{bmatrix} \Psi_{i11} & \Psi_{i12} \\ \Psi_{i12} & \Psi_{i22} \end{bmatrix}$$

where  $\Psi_{i11} = [\psi_{i1t}^q]$  is the variance of the quantity error,

$$\Psi_{i12} = \begin{bmatrix} \sigma_{11}^{qc} \\ \sigma_{12}^{qc} \\ \sigma_{13}^{qc} \end{bmatrix}$$

is the covariance between choice and quantity errors, and

$$\Psi_{i22} = \begin{bmatrix} \psi_{i1t}^c + \psi_{i2t}^c - 2\sigma_{12}^c & | & \psi_{i1t}^c + \psi_{i3t}^c - 2\sigma_{13}^c & | \\ \psi_{i1t}^c - \sigma_{13}^c - \sigma_{12}^c + \sigma_{23}^c & | & \psi_{i1t}^c + \psi_{i3t}^c - 2\sigma_{13}^c & | \\ \psi_{i1t}^c - \sigma_{14}^c - \sigma_{12}^c + \sigma_{24}^c & | & \psi_{i1t}^c - \sigma_{14}^c - \sigma_{13}^c + \sigma_{34}^c & | \\ \psi_{i1t}^c + \psi_{i4t}^c - 2\sigma_{14}^c & & & \end{bmatrix}$$

are the covariances of the utility difference variables,  $v_{ijdt}$ , in the choice model.

Note that the covariances between choice and quantity errors are nonzero *within* a brand, but are assumed to be zero *across* brands.

The likelihood expressions for brands 2, 3, and 4 are derived in the same fashion. The log-likelihood for the data can therefore be written as:

$$LL = \sum_{i=1}^N \sum_{j=1}^4 \sum_{t=1}^{T_i} \ln L_{ijt} \quad (A-10)$$

where  $N$  is the number of households in the sample and  $T_i$  is the number of purchase occasions for household  $i$ .

Appendix B: Conditional Moments of  $Q_{i1t}$

Conditional Expectation of  $Q_{i1t}$

From Equations (A-7) and (A-8), the conditional expectation of  $Q_{i1t}$  given choice of brand 1 is

<sup>12</sup>Conceptually it is straightforward to extend the likelihood expression for more than four brands. We restricted the number of brands to four for ease of exposition and because our application involves four major brands.

$$\begin{aligned}
 \tau_{11t} &= E(Q_{11t} | v_{112t} > \mu_{12t}^c - \mu_{11t}^c, v_{113t} > \mu_{13t}^c - \mu_{11t}^c) \\
 &> \mu_{13t}^c - \mu_{11t}^c, v_{114t} > \mu_{14t}^c - \mu_{11t}^c) \\
 &= \mu_{11t}^q + E(\zeta_{11t}^q | v_{112t} > \mu_{12t}^c - \mu_{11t}^c, v_{113t} > \mu_{13t}^c - \mu_{11t}^c) \\
 &> \mu_{13t}^c - \mu_{11t}^c, v_{114t} > \mu_{14t}^c - \mu_{11t}^c). \tag{B-1}
 \end{aligned}$$

Because  $\zeta_{11t}^q$ ,  $v_{112t}$ ,  $v_{113t}$ , and  $v_{114t}$  follow a multivariate normal distribution, the conditional density of  $(\zeta_{11t}^q | v_{112t}, v_{113t}, v_{114t})'$  is also multivariate normal. Hence we can write

$$\begin{aligned}
 E(\zeta_{11t}^q | \cdot) &= \Psi_{112}^{-1} \Psi_{122}^{-1} E(v_{11t} | v_{112t} > \mu_{12t}^c - \mu_{11t}^c, v_{113t} > \mu_{13t}^c - \mu_{11t}^c, v_{114t} > \mu_{14t}^c - \mu_{11t}^c) \\
 &= \sigma_1^q \mathbf{1}' \Psi_{122}^{-1} E(\mathbf{v}_{11t} | \cdot) \\
 &= \sigma_1^q W_{11t}(\Theta^c), \tag{B-2}
 \end{aligned}$$

where  $\mathbf{v}_{11t} = (v_{112t}, v_{113t}, v_{114t})'$ . Note that  $W_{11t}(\Theta^c) = \mathbf{1}' \Psi_{122}^{-1} E(v_{11t} | \cdot)$  only depends on the choice parameter vector  $\Theta^c = (\gamma^c, \Sigma^c)$ .

The elements of  $E(v_{11t} | \cdot)$  are obtained using general results on the moments of the truncated multivariate normal distribution derived by Tallis (1961, p. 225). Transforming  $\mathbf{v}_{11t}$  to a standard multinormal vector  $\mathbf{z}_{11t}^*$  and applying Tallis' formulae, we can show, for example, that

$$\begin{aligned}
 E(v_{112t} | \cdot) &= \frac{\sqrt{\psi_{11t}^c + \psi_{12t}^c - 2\sigma_{12}^c}}{\alpha_1} \\
 &E(z_{12}^* | z_{12}^* > a_{12}^*, z_{13}^* > a_{13}^*, z_{14}^* > a_{14}^*) \\
 &= \frac{\sqrt{\psi_{11t}^c + \psi_{12t}^c - 2\sigma_{12}^c}}{\alpha_1} \{ \phi(a_{12}) \Phi_2(A_{23}, A_{24}; \rho_{34.2}) \\
 &+ \rho_{23} \phi(a_{13}) \Phi_2(A_{32}, A_{34}; \rho_{24.3}) \\
 &+ \rho_{24} \phi(a_{14}) \Phi_2(A_{42}, A_{43}; \rho_{23.4}) \} \tag{B-3}
 \end{aligned}$$

where

$$\begin{aligned}
 a_{1s} &= \frac{\mu_{1st}^c - \mu_{11t}^c}{\sqrt{\psi_{11t}^c + \psi_{1st}^c - 2\sigma_{1s}^c}}, s = 2 \dots 4, \\
 \rho_{ls} &= \text{correlation coefficient between } v_{11t} \text{ and } v_{1st}, s, l = 2 \dots 4, \\
 \mathbf{z}_{11t}^* &= (z_{12}^*, z_{13}^*, z_{14}^*)' \\
 &= \text{trivariate standard normal vector with covariance elements } \rho_{ls}, \\
 A_{1s} &= \frac{a_{1s} - \rho_{1s} a_{11}}{\sqrt{1 - \rho_{1s}^2}}, \\
 \rho_{sr,l} &= \text{partial correlation between } v_{11st} \text{ and } v_{11rt}, \text{ for fixed } v_{11lt}, s, r, l = 2 \dots 4, \\
 \Phi_2(\cdot) &= \text{standard bivariate normal distribution function,} \\
 \alpha_1 &= \text{choice probability of brand 1.}
 \end{aligned}$$

There is a similar expression for the other elements  $E(v_{1idt} | \cdot)$ ,  $d = 3, 4$ .

**Conditional Variance of  $Q_{11t}$**

Using Equations (A-7) and (A-8) and the properties of the multivariate normal distribution, the conditional variance of  $Q_{11t}$  given choice of brand 1 may be written as

$$\begin{aligned}
 \varphi_{11t}^2 &= \text{Var}(\zeta_{11t}^q | v_{112t} > \mu_{12t}^c - \mu_{11t}^c, v_{113t} > \mu_{13t}^c - \mu_{11t}^c, v_{114t} > \mu_{14t}^c - \mu_{11t}^c) \\
 &= \text{Var}(\Psi_{112}' \Psi_{122}^{-1} \mathbf{v}_{11t} | v_{112t} > \mu_{12t}^c - \mu_{11t}^c, v_{113t} > \mu_{13t}^c - \mu_{11t}^c, v_{114t} > \mu_{14t}^c - \mu_{11t}^c) \\
 &= (\sigma_1^q)^2 \mathbf{1}' \Psi_{122}^{-1} \mathbf{S}_{11t}(\Theta^c) \Psi_{122}^{-1} \mathbf{1}, \tag{B-4}
 \end{aligned}$$

where  $\mathbf{v}_{11t} = \mathbf{1}' \Psi_{122}^{-1} \mathbf{S}_{11t}(\Theta^c) \Psi_{122}^{-1} \mathbf{1}$  is a function of the choice parameters and  $\mathbf{S}_{11t}$  is the covariance matrix of  $(\mathbf{v}_{11t} | \cdot)$ . We obtain the elements of  $\mathbf{S}_{11t}$  using the difference

$$E(v_{11jt} v_{11kt} | \cdot) - E(v_{11jt} | \cdot) E(v_{11kt} | \cdot), \quad j, k = 2, 3, 4.$$

We determine the conditional second moments  $E(v_{11jt} v_{11kt} | \cdot)$  using Tallis' (1961) results. These are given by

$$\begin{aligned}
 E((v_{112t})^2 | \cdot) &= \frac{\psi_{11t}^c + \psi_{12t}^c - 2\sigma_{12}^c}{\alpha_1} \\
 &\cdot \{ \alpha_1 + a_{12} \phi(a_{12}) \Phi_2(A_{23}, A_{24}; \rho_{34.2}) \\
 &+ \rho_{23}^2 a_{13} \phi(a_{13}) \Phi_2(A_{32}, A_{34}; \rho_{24.3}) \\
 &+ \rho_{24}^2 a_{14} \phi(a_{14}) \Phi_2(A_{42}, A_{43}; \rho_{23.4}) \\
 &+ \rho_{23} (1 - \rho_{23}^2) \phi_2(a_{12}, a_{13}; \rho_{23}) \Phi(A_{23}^3) \\
 &+ \rho_{24} (1 - \rho_{24}^2) \phi_2(a_{12}, a_{14}; \rho_{24}) \Phi(A_{24}^3) \\
 &+ \phi_2(a_{13}, a_{14}; \rho_{34}) [\rho_{23} \rho_{24} - \rho_{23} \rho_{34}] \Phi(A_{42}^3) \\
 &+ \rho_{24} (\rho_{23} - \rho_{34} \rho_{24}) \Phi(A_{32}^4) \}, \tag{B-5}
 \end{aligned}$$

and

$$\begin{aligned}
 E(v_{112t} v_{113t} | \cdot) &= \frac{\sqrt{(\psi_{11t}^c + \psi_{12t}^c - 2\sigma_{12}^c)(\psi_{11t}^c + \psi_{13t}^c - 2\sigma_{13}^c)}}{\alpha_1} \\
 &\cdot \{ \alpha_1 \rho_{23} + \rho_{23} a_{12} \phi(a_{12}) \Phi_2(A_{23}, A_{24}; \rho_{34.2}) \\
 &+ \rho_{23} a_{13} \phi(a_{13}) \Phi_2(A_{32}, A_{34}; \rho_{24.3}) \\
 &+ \rho_{24} \rho_{34} a_{14} \phi(a_{14}) \Phi_2(A_{42}, A_{43}; \rho_{23.4}) \\
 &+ (1 - \rho_{23}^2) \phi_2(a_{12}, a_{13}; \rho_{23}) \Phi(A_{34}^3) \\
 &+ \rho_{24} (1 - \rho_{24}^2) \phi_2(a_{13}, a_{14}; \rho_{34}) \Phi(A_{42}^3) \\
 &+ \phi_2(a_{12}, a_{13}; \rho_{14}) [(\rho_{34} - \rho_{24} \rho_{23}) \Phi(A_{43}^2) \\
 &+ \rho_{24} (\rho_{23} - \rho_{24} \rho_{34}) \Phi(A_{23}^4) \}, \tag{B-6}
 \end{aligned}$$

where

$$A_{1s}^r = \frac{a_{1s} - \beta_{sr}a_{1r} - \beta_{sl,r}a_{1l}}{\sqrt{(1 - \rho_{sr}^2)(1 - \rho_{sl,r}^2)}}$$

and  $\beta_{sr,l}$  and  $\beta_{sl,r}$  are the partial regression coefficients of  $z_{1s}$  on  $z_{1r}$  and  $z_{1l}$  respectively. There are similar expressions for the remaining elements  $E(\nu_{1j}|\nu_{1k})$ ,  $j, k = 2, 3, 4$ .

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