TÜLIN ERDEM and BAOHONG SUN*

The authors investigate and find evidence for advertising and sales promotion spillover effects for umbrella brands in frequently purchased packaged product categories. The authors also capture the impact of advertising (as well as use experience) on both utility mean and variance across two categories. They show that variance of the random component of utility declines over time on the basis of advertising (and use experience) in either category. This constitutes the first empirical evidence for the uncertainty-reducing role of advertising across categories for umbrella brands.

An Empirical Investigation of the Spillover Effects of Advertising and Sales Promotions in Umbrella Branding

Many companies widely practice umbrella branding. Also, a fair amount of managerial research argues that umbrella branding generates savings in brand development and marketing costs over time (e.g., Lane and Jacobson 1995; Tauber 1981, 1988) and enhances marketing productivity (e.g., Rangaswamy, Burke, and Oliver 1993).

Wernerfelt (1988) has shown analytically that a multiproduct firm can use its brand name as a bond for quality when it introduces a new-experience product. Umbrella branding is posited to both increase expected quality (Wernerfelt 1988) and reduce consumer risk (Montgomery and Wernerfelt 1992). Consumers' use experience in one product category needs to affect their perceptions of quality in another for umbrella branding to serve as a credible signal of a new-experience product's quality, because a false signal would be costly if the quality of the extension turned out to be poor. Experimental research has shown some evidence that the parent brand's perceived quality affects the extension evaluations (Aaker and Keller 1990) and vice versa, which indicates that brand equity dilution may occur (Loken and Roedder John 1993).

Although the cross-category learning effects for umbrella brands are a necessary condition for umbrella branding to function as a signal (Erdem 1998), the learning effects alone may be insufficient for umbrella branding to generate savings in marketing costs and enhance marketing productivity over time. To increase savings in marketing costs over time, the marketing mix, such as advertising and sales promotions, must be more effective for umbrella brands than for other brands. For example, Tauber (1981) suggests that umbrella branding can create advertising efficiencies. Leigh (1984) finds some experimental evidence for better recall and recognition performance for umbrella branding than other branding strategies. Yet there is surprisingly little empirical work on advertising and/or any other marketing-mix synergies for umbrella brands.

The objectives of this study are twofold. First, we test for marketing-mix strategy spillover effects of umbrella brands in frequently purchased packaged product categories. We are especially interested in testing for own- and cross-effects of advertising, that is, whether advertising in one product category affects sales in another product category for umbrella brands. However, we investigate the cross-category effects of all marketing-mix effects, including price, coupon availability, display, and feature. Another related objective is to shed some light on the magnitude of any effects that may exist. We seek to answer the following questions: (1) What is the impact of the cross-effects on sales? (2) How large are the cross-effects of the marketing mix elements in relation to the own-effects? and (3) Which marketing-mix elements seem to reveal higher cross-effects?

Second, we explore the dynamics behind the advertising spillover effects. Similar to use experience, advertising spillover effects occur for various reasons, but they may also transpire because of the uncertainty reduction. More specifically, we examine whether there is a reduction in consumer uncertainty in one category due to advertising of the

*Tülin Erdem is an associate professor, University of California, Berkeley (e-mail: erdem@haas.berkeley.edu). Baohong Sun is an assistant professor, Kenan-Flagler Business School, University of North Carolina, Chapel Hill (e-mail: sunb@bschool.unc.edu). The authors thank the three anonymous *JMR* reviewers for their constructive feedback. The authors also thank Andrew Ainslie and Michael Keane for their suggestions in regard to the updating mechanism of the stochastic component of utility employed in this article. This research was supported by National Science Foundation grant SBR-9812067 granted to Tülin Erdem.

umbrella brand in another category over time. If uncertainty exists and advertising reduces consumer uncertainty about products, advertising is expected to shift both utility mean and variance. To model and test for both utility mean– and utility variance–shifting cross-effects of use experience and advertising, we develop a novel and parsimonious approach. Our approach enables us to test whether there is any evidence for the uncertainty-reducing role of advertising across categories.

We use ACNielsen scanner panel data on two categories—toothpaste and toothbrushes—to test for marketing-mix synergies for umbrella brands. For the first time in the literature, on the basis of our analysis of revealed preference data, we find evidence for advertising spillover effects for umbrella brands. Furthermore, we find that advertising (as well as use experience) in one category serves as a mechanism of reducing uncertainty in the other category for umbrella brands. In addition, our results indicate that there are spillover effects of price, coupon availability, and display. Feature cross-effects exist only in the toothbrush category.

The rest of the article is organized as follows: In the first section, we briefly discuss the relevant literature. In the second section, we outline the proposed model and the estimation method. In the third section, we briefly describe the data. We then outline the results and conclude the article with implications and a discussion of further research.

LITERATURE REVIEW

Previous research in marketing has studied the effects of sales promotions across categories for complementary and substitute products (e.g., Mulhern and Leone 1991) and multicategory choices (e.g., Bell and Lattin 1998; Manchanda, Ansari, and Gupta 1999). A separate stream of literature focuses on cross-category traits of consumer behavior and finds that consumer price sensitivities (Ainslie and Rossi 1998; Erdem 1998) or sensitivities to state dependence (Erdem 1998; Seetharaman, Ainslie, and Chintagunta 1999) can be correlated across categories.

However, there is surprisingly little published research with respect to cross-category effects in choice for umbrella brands. Erdem and Winer (1999) have shown that brand preferences can be correlated across categories for umbrella brands. Erdem (1998) has studied how consumers' experience in one category may affect their quality perceptions in another category for umbrella brands. In a two-category context, Erdem has shown that consumer mean quality beliefs, as well as the variance of these quality beliefs, may be updated through experience in either category for umbrella brands. Thus, Erdem studied only cross-category use experience effects.

Specifically, Erdem (1998) does not study any promotion or advertising effects, neither own-category nor cross-category, which is the topic of this article. Therefore, she does not study and answer any questions about the existence and magnitude of cross-advertising and promotion effects for umbrella brands. Furthermore, her model does not incorporate purchase incidence and coincidence in choice, that is, the possibility that the stochastic component of the utility function could be correlated across categories. In addition, Erdem's approach only allows for use experience effects due to learning, whereas the approach we take in this article allows for both learning effects and other sources through which use experience may affect current choices. Furthermore, the approach Erdem takes to incorporate the impact of use experience on utility variance is difficult to apply to settings in which cross-category variance reduction effects can be due to other variables as well (such as advertising). The approach taken in this article provides a more parsimonious and novel way to incorporate such effects. Finally, we allow for more complex heterogeneity structures in this article than Erdem does.

Manchanda, Ansari, and Gupta (2000) also find some preliminary evidence for spillover effects in store promotional activity for umbrella brands; however, they have not analyzed advertising and they have not allowed for choice dynamics.

THE MODEL

Utility Specification

Consider a set of consumers $I = \{i|i = 1, 2, ..., I\}$ that, on each purchase occasion, makes purchases from none, one, or both of two distinct product categories $m = 1, 2$, where I is the number of consumers. A nonempty subset, but not necessarily all, of these consumers makes purchases from both of the categories. Suppose that for both product categories, the purchases of the consumers are observed over the period $T = \{t|t = 1, 2, ..., T\}$, where T is the time span of the period and t denotes the week. Let $J = \{j|j = 1, 2, ..., J\}$ be the set of brand options available, where $j = 1, \ldots, J$ brands are available in at least one of the two categories and J is the number of brands. Note that we set $j = 0$ to indicate the no-purchase option (choice).

Let K_{mj}, $m = 1, 2$, be an indicator variable such that $K_{mj} = 1$ if brand j is available in category m, and $K_{mj} = 0$ otherwise. Also let D_{mijt}, $m = 1, 2$, be an indicator variable such that if consumer i purchases brand j at time t in category m, $D_{mijt} = 1$, and $D_{mijt} = 0$ otherwise. Finally, denote the utility consumer i derives from purchasing brand j in category m at time (week) t by U_{mijt}, which is postulated to be

$$(1)\quad \begin{aligned} U_{mijt} = {} & \alpha_{mij} + \beta_{mi}PR_{mijt} + \gamma_{mi}AD_{mijt} + \lambda_{mi}DISP_{mijt} \\ & + \tau_{mi}FEAT_{mijt} + \vartheta_{mi}CAV_{mijt} + \kappa_{mi}UE_{mijt} \\ & + K_{3-m,j}(\xi_{mi}PR_{3-m,i,j,t} + \iota_{mi}AD_{3-m,i,j,t} \\ & + \mu_{mi}DISP_{3-m,i,j,t} + \nu_{mi}FEAT_{3-m,i,j,t} \\ & + \zeta_{mi}CAV_{3-m,i,j,t} + \omega_{mi}UE_{3-m,i,j,t}) + \varepsilon_{mijt}, \end{aligned}$$

where PR_{mijt} is the price paid for brand j in category m by consumer i at t, AD_{mijt} is the advertising stock variable for consumer i with respect to brand j in category m at t, $DISP_{mijt}$ is the display dummy, $FEAT_{mijt}$ is the in-store ad dummy, CAV_{mijt} is the coupon availability variable, and UE_{mijt} is the use experience of brand j in category m consumer i has at t. Equation 1 suggests that if brand j is available in both categories, the utility of purchasing brand j in one of the categories will also depend on the price, coupon availability, advertising, display, feature, and use experience associated with the same brand name in the other category.[1]

[1]Note that in Equation 1, cross-effects are specified for umbrella brands only. In the empirical analysis, to ensure that the effects exist for only umbrella, we also tested whether such effects exist for other brands as well, and we did not find evidence for such effects.

The parameters in Equation 1 are as follows: α_{mij} is the consumer- and brand-specific constant (brand preference), and β_{mi} is the consumer-specific price coefficient. Moreover, γ_{mi}, λ_{mi}, τ_{mi}, ϑ_{mi}, and κ_{mi} are the consumer-specific advertising, display, feature, coupon, and use experience coefficients in category m (we label these own-effects response coefficients), whereas, ξ_{mi}, ι_{mi}, μ_{mi}, ν_{mi}, ζ_{mi}, and ω_{mi} are the price, advertising, display, feature, coupon availability, and use experience coefficients of the price, advertising, display, feature, and use experience variables in the other category, respectively (we label these cross-effects response coefficients). Similar to Erdem and Keane (1996), we specify i's utility from not purchasing any brand in category m at t as[2]

$$(2) \qquad U_{mi0t} = \alpha_{m0} + \text{TREND}_m t + \varepsilon_{m0t},$$

where TREND_m is the time trend coefficient, and for identification purposes we set

$$(3) \qquad \alpha_{m0} = 0, \qquad m = 1, 2.$$

The use experience variable, UE_{mijt}, in Equation 1 is defined as the exponentially smoothed weighted average of past purchases, as in Guadagni and Little's (1983) brand loyalty variable. Its decay parameter is denoted by DU_m. Similarly, AD_{mijt} is defined as the exponentially smoothed weighted average of past aggregate gross rating points (GRPs).[3] Its decay parameter is denoted by DA_m. The AD_{mijt} is updated on a weekly basis. Note that γ_{mi} (and η_{mi}), the coefficient on the advertising stock variable, embeds both a consumer's television commercial viewing habits and responsiveness to the advertisements, conditional on having seen them. Because advertising effectiveness in the context of television advertisements depends on television and commercial viewing habits of consumers, we can justify that γ_{mi} (and ι_{mi}) represents advertising responsiveness at the individual level.[4]

We define the DISP variable such that $DISP_{mijt} = 1$ if a display is available for brand j in category m in the store that consumer i visits at t, whereas $DISP_{mijt} = 0$ otherwise. Similarly, we define the FEAT variable such that $FEAT_{mijt} = 1$ if a feature is available for brand j in category m in the store that consumer i visits at t, whereas $FEAT_{mijt} = 0$ otherwise. Finally, CAV_{mijt} is the average value of the store's and manufacturer's coupons available for brand j in category m in the store that consumer i visits at t. It includes the zero value for nonavailable coupons (Keane 1997b). We introduce this variable to avoid the endogeneity problem caused by including coupons redeemed in the utility specification. Last, ε_{mijt} in Equation 1 denotes the time-varying stochastic component of utility that is known by the consumer but not observable by the analyst.

We should note that the cross-effects specified in Equation 1 may exist for several reasons. First, price cuts, coupons, advertising, displays, and features in one category may remind the consumer about the umbrella brand and therefore increase the likelihood of their choosing that brand in another category, conditional on product category decision. In the case of promotional tools such as displays, the promotion of the umbrella brand in one category may help promote the umbrella brand in consumers' consideration sets in the second category, in which the brand is not promoted, as well. Advertising can be expected to increase general brand awareness of individual products that share the same brand name. Cross-category use experience effects may be due to habit formation.

Second, the effects of use experience and advertising on consumer uncertainty may cause use experience and advertising spillover effects. If use experience affects quality beliefs, both the mean and variance of these beliefs may change on the basis of use experience. Therefore, if use experience affects consumer uncertainty, we should expect it to affect both the utility mean and variance in a reduced-form model. The same rationale holds for advertising. Erdem and Keane (1996) have shown that in the context of one category, both use experience and advertising affect both mean and variance of quality perceptions. Therefore, if advertising spillover effects are partly due to the effect of advertising on consumer uncertainty, we should expect utility variance (that is, the variance of the random component of utility) to decline over time on the basis of advertising.

We capture these utility variance effects by adopting a novel approach. Specifically, we allow for not only the "random" components of utility to be correlated across categories but also the variances of the random components for umbrella brands to be updated on the basis of past purchases and advertising associated with umbrella brands in either category. We cover this issue in more detail subsequently. It may suffice to state that we attempt to capture the effect of use experience and advertising as a shifter of both utility mean and variance; the latter effect should occur mainly because the consumer uncertainty decreases over time on the basis of past purchases and advertising.

Heterogeneity Specification

It is well established that not accounting for unobserved heterogeneity can bias parameter estimates (Heckman 1981; Rossi and Allenby 1993). In this article, we account for unobserved heterogeneity as well. To do so, we assume that brand preferences for each category $A_{mi} = (\alpha_{mi1}, \alpha_{mi2}, \ldots, \alpha_{miJ})^T$; own-effects response coefficients $B_{mi} = (\beta_{mi}, \gamma_{mi}, \lambda_{mi}, \tau_{mi}, \vartheta_{mi}, \kappa_{mi})^T$; and cross-effects response coefficients $C_{mi} = (\xi_{mi}, \iota_{mi}, \mu_{mi}, \nu_{mi}, \zeta_{mi}\ \omega_{mi})^T$, m = 1, 2, where the superscript T denotes the transpose, are normally distributed with the following mean vector and covariance matrix:

[2]Similar to Erdem and Keane (1996), our purpose is to control for purchase incidence rather than explicitly model purchase incidence decisions.

[3]An alternative to GRP data is television exposure data; however, television exposure data are not available because ACNielsen discontinued the collection of such data in the early 1990s. Television exposure data have the advantage of having the estimated advertising coefficient reflect advertising responsiveness only because the advertising variable itself will capture the television/commercial viewing habits. However, the television exposure data are noisy as well, because we only knew that the television was tuned to that channel during the airing of a particular commercial. One advantage of the GRP data, in contrast, is that GRP is under the direct control of the firm whereas television exposure is not. Therefore, firms are more interested in models that use GRP data (Abe 1997). Finally, Tellis and Weiss (1995) find that advertising effectiveness results are not sensitive to the types of advertising measures.

[4]We also have GRP data for different "dayparts" (e.g., prime time versus late morning). When we used these data and estimated Equation 1 with separate coefficients for each daypart, we obtained larger advertising coefficients for certain dayparts than others, as we would expect, but the main results are the same whether the daypart data are used or not.

$$(4)\quad \begin{bmatrix} A_{1i} \\ B_{1i} \\ C_{1i} \\ A_{2i} \\ B_{2i} \\ C_{2i} \end{bmatrix} \sim N\left\{\begin{bmatrix} A_1 \\ B_1 \\ C_1 \\ A_2 \\ B_2 \\ C_2 \end{bmatrix}, \begin{bmatrix} \Sigma A_1 & \Pi_{A_1B_1} & \Pi_{A_1C_1} & \Pi_{A_1A_2} & \Pi_{A_1B_2} & \Pi_{A_1C_2} \\ \Pi_{A_1B_1} & \Sigma B_1 & \Pi_{B_1C_1} & \Pi_{B_1A_2} & \Pi_{B_1B_2} & \Pi_{B_1C_2} \\ \Pi_{A_1C_1} & \Pi_{B_1C_1} & \Sigma C_1 & \Pi_{C_1A_2} & \Pi_{C_1B_2} & \Pi_{C_1C_2} \\ \Pi_{A_1A_2} & \Pi_{B_1A_2} & \Pi_{C_1A_2} & \Sigma A_2 & \Pi_{A_2B_2} & \Pi_{A_2C_2} \\ \Pi_{A_1B_2} & \Pi_{B_1B_2} & \Pi_{C_1B_2} & \Pi_{A_2B_2} & \Sigma B_2 & \Pi_{A_2C_2} \\ \Pi_{A_1C_2} & \Pi_{B_1C_2} & \Pi_{C_1C_2} & \Pi_{A_2C_2} & \Pi_{A_2C_2} & \Sigma C_2 \end{bmatrix}\right\}.$$

The vectors A_1, B_1, C_1 are the means in Category 1 and the vectors A_2, B_2, C_2 are the means in Category 2. The block diagonal matrices ΣA_1, ΣB_1, ΣC_1, ΣA_2, ΣB_2, and ΣC_2 are the covariance matrices of A_{1i}, B_{1i}, C_{1i}, A_{2i}, B_{2i}, and C_{2i}, respectively. The diagonal elements of ΣA_1, ΣB_1, ΣC_1, ΣA_2, ΣB_2, and ΣC_2 themselves contain the variances of the corresponding heterogeneity distributions. Finally, Π are the appropriate covariance matrices.

Within-Category Correlations

Given the large number of covariances to be estimated as shown in Equation 4, we allow only a subset of these covariances to be nonzero for parsimony.[5] We allow heterogeneity in all brand-specific constants and allow own and cross marketing-mix response and use experience coefficients; however, we estimate and report in the "Results" section of the article only the following covariances (correlations) among the heterogeneity distributions: (1) correlations among the brand specific constants and price (as well as advertising) sensitivities, (2) pairwise correlations between own price (and advertising) sensitivities and all other marketing-mix sensitivities (e.g., display), and (3) pairwise correlations between own price (and advertising) sensitivities and use experience.

Cross-Category Correlations

Ainslie and Rossi (1998) suggest that consumer sensitivities to marketing variables (own-effects of the marketing mix in our model) may be correlated across categories. Therefore, a person who is more price sensitive than the average consumer in one category can be also more price sensitive than the average consumer in another category. Therefore, we also estimate Π_{B1B2} (the covariance matrix of B_1 and B_2). This means that we permit consumer price, advertising, display, feature, coupon, and use experience sensitivities to covary across the two categories. For example, a consumer who is more advertising sensitive than the average consumer in the toothbrush category may also tend to be more advertising sensitive than the average consumer in the toothpaste category. The corresponding cross-category correlations can be calculated from the covariance matrix Π. We denote these cross-category correlations by Λ.[6]

Choice Probabilities

Let us rewrite Equation 1 for each category m, where m = 1, 2, as

$$(5)\qquad U_{mijt} = V_{mijt} + \varepsilon_{mijt},$$

where V_{mijt} is the "deterministic" part of the utility.

Let θ denote the vector of parameters $(A_1, A_2, B_1, B_2, C_1, C_2, d(\Sigma A_1), d(\Sigma A_2), d(\Sigma B_1), d(\Sigma B_2), d(\Sigma C_1), d(\Sigma C_2), w(\Pi))^T$. The vectors $d(\Sigma A_1)$, $d(\Sigma A_2)$, $d(\Sigma C_1)$, and $d(\Sigma C_2)$ contain the diagonal elements of the corresponding matrices (i.e., the variances of the heterogeneity distributions of brand preferences and cross-effects response coefficients). The vectors $d(\Sigma B_1)$ and $d(\Sigma B_2)$ contain the diagonal elements (variances of own-effects response coefficients) of the corresponding matrices, as well as the off-diagonal elements, or covariances, that we allowed to be nonzero. Finally, the vector $w(\Pi)$ contains the covariances among the brand-specific constants and advertising and price sensitivities, as well as cross-category covariances to be estimated. Note that though we used the covariance matrices in defining the parameter vector for notational convenience, we estimate the corresponding standard deviations and correlations introduced previously, instead of the variances and covariances.

Recall that all coefficients in Equation 1 are allowed to be heterogeneous across consumers, and their distributions are given in Equation 4. Let φ_i denote the multivariate standard normal vector that generates these coefficients. To be able to write down the choice probabilities, we need to specify a distribution for ε_{mijt}.

We assume that ε_{mijt} $j \in J$ is given by

$$(6)\qquad \varepsilon_{mijt} = y_{mijt} - E_t[y_{mijt}],$$

where y_{mijt} is the generator of ε_{mijt}, whose prior distribution is

$$(7)\qquad \begin{bmatrix} y_{1ij0} \\ y_{2ij0} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right).$$

Note that $E_t[.]$ indicates expectation conditional on the information at time t. Equations 6 and 7 indicate that the means of the random components are always zero, whereas the assumption is that the initial variances are one and the initial covariance between the random components is ρ.

A parsimonious and new way of capturing the utility variance–shifting role of use experience and advertising is to allow the initial utility variance, which we set to unity, to be updated conditional on past purchases. Neither advertising's

[5]However, in the empirical analysis, we tested the sensitivity of our results to the assumptions made about covariance structure by allowing more covariances (correlations) to be nonzero. For example, we estimated the covariances between brand-specific constants, a few covariances among the cross-response coefficients, and so forth, but these did not improve the model fit significantly and did not change the parameter estimates.

[6]Finally, note that we adopt the recent classical inference techniques to model and estimate unobserved heterogeneity. An alternative approach would have been Bayesian techniques (e.g., Rossi, McCulloch, and Allenby 1996). However, the main advantage of such techniques is the ability to provide household-level parameter estimates, which is particularly useful if the research objective includes micromarketing implications, which is beyond the scope of this article.

impact on the consumer utility mean nor its impact on the consumer utility variance across categories for umbrella brands has been empirically verified in previous work.

To capture the effects of both use experience and advertising on the variance of the random component, that is, utility variance, let the information obtained by consumer i by purchasing brand j before time t from category m be denoted by x_{mijt}. This information can be about attributes, including quality, or match information between consumer tastes and product offerings and the like, which are not observed by the analyst. Let x_{mijt} be given by

$$(8) \qquad x_{mijt} = y_{mijt} + \delta_{mijt},$$

where δ_{ijtm} is an i.i.d. random error term that reflects the level of noise in the information obtained. We suppose that

$$(9) \qquad \delta_{mijt} \sim N(0, \sigma_{\delta m}{}^2).$$

Note that additional information comes from weekly advertisements. Denoting this information with z_{mijt} , we let

$$(10) \qquad z_{mijt} = y_{mijt} + \eta_{mijt},$$

where η_{ijtm} is an i.i.d. random error term that reflects the level of noise in the information from the advertisement. It is given by

$$(11) \qquad \eta_{mijt} \sim N(0, \sigma_{\eta m}{}^2).$$

Given these, we then assume that the random component of utility is updated according to Bayesian updating rules and invoke the Kalman filter for updating the distribution of y_{mijt} and therefore of ε_{mijt}. There is no updating for j = 0, which corresponds to no purchase. To derive the Kalman filter, we regress

$$y_{mijt} - E_{t-1}[y_{mijt}]$$

on

$$x_{mijt} - E_{t-1}[x_{mijt}] \text{ and } z_{mijt} - E_{t-1}[z_{mijt}],\ m = 1, 2$$

by suppressing the intercept, and we obtain the following updating formulas for the expectations:

$$\begin{aligned}(12) \quad E_t[y_{mijt}] = {} & E_{t-1}[y_{mijt}] + b_{1mijt}\{x_{mijt} - E_{t-1}[y_{mijt}]\} \\ & + b_{2mijt}\{x_{3-m,i,j,t} - E_{t-1}[y_{3-m,i,j,t}]\} \\ & + b_{3mijt}\{z_{m,i,j,t} - E_{t-1}[z_{m,i,j,t}]\} \\ & + b_{4mijt}\{z_{3-m,i,j,t} - E_{t-1}[z_{3-m,i,j,t}]\},\end{aligned}$$

where b_{kmijt}, k = 1, 2 and m = 1, 2 are solved from

$$(13) \quad \begin{bmatrix} D_{m,i,j,t-1}\sigma_{m,i,j,t-1}{}^2 + \sigma_{\delta m}{}^2 & D_{m,i,j,t-1}\sigma_{12,i,j,t-1} & D_{m,i,j,t-1}\sigma_{m,i,j,t-1}{}^2 & D_{m,i,j,t-1}\sigma_{12,i,j,t-1} \\ D_{3-m,i,j,t-1}\sigma_{12,i,j,t-1} & D_{3-m,i,j,t-1}\sigma_{3-m,i,j,t-1}{}^2 + \sigma_{\delta,3-m}{}^2 & D_{3-m,i,j,t-1}\sigma_{12,i,j,t-1} & D_{3-m,i,j,t-1}\sigma_{3-m,i,j,t-1}{}^2 \\ D_{m,i,j,t-1}\sigma_{m,i,j,t-1}{}^2 & D_{3-m,i,j,t-1}\sigma_{12,i,j,t-1} & \sigma_{m,i,j,t-1}{}^2 + \sigma_{\eta m}{}^2 & \sigma_{12,i,j,t-1} \\ D_{m,i,j,t-1}\sigma_{12,i,j,t-1} & D_{3-m,i,j,t-1}\sigma_{3-m,i,j,t-1}{}^2 & \sigma_{12,i,j,t-1} & \sigma_{3-m,i,j,t-1}{}^2 + \sigma_{\eta,3-m}{}^2 \end{bmatrix} \begin{bmatrix} b_{1mijt} \\ b_{2mijt} \\ b_{3mijt} \\ b_{4mijt} \end{bmatrix} = \begin{bmatrix} D_{m,i,j,t-1}\sigma_{m,i,j,t-1}{}^2 \\ D_{3-m,i,j,t-1}\sigma_{12,i,j,t-1} \\ \sigma_{m,i,j,t-1}{}^2 \\ \sigma_{12,i,j,t-1} \end{bmatrix},$$

and with Equation 12, the updating formulas for the variances are obtained from

$$(14) \quad \sigma_{mijt}{}^2 = E_t\left\{\left[y_{mijt} - E_t(y_{mijt})\right]^2\right\}, \qquad m = 1, 2$$

$$\sigma_{12ijt} = E_t\left\{\left[y_{1ijt} - E_t(y_{1ijt})\right]\left[y_{2ijt} - E_t(y_{2ijt})\right]\right\}.$$

Note that the preceding equations suggest that the higher the precision of information from use experience ($1/\sigma^2_{\delta n}$) and advertising ($1/\sigma^2_{\eta m}$) are (or the lower the use experience variability, $\sigma^2_{\delta n}$, and advertising variability, $\sigma^2_{\eta m}$, are), the more consumers will update.

Given Equations 12 to 14, the distribution of ε_{mijt}, m = 1, 2 at time t is given by

$$(15) \quad \begin{bmatrix} \varepsilon_{1ijt} \\ \varepsilon_{2ijt} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{1ijt}{}^2 & \sigma_{12ijt} \\ \sigma_{12ijt} & \sigma_{2ijt}{}^2 \end{bmatrix}\right), \qquad j = 1, 2, \ldots, J.$$

We then can write the choice probabilities conditional on θ and φ_i as

$$(16) \quad \text{Prob}_{it}(D_{1ijt} = 1, D_{2ikt} = 1; \theta, \varphi_i) = \Phi_{tjk}(\theta, \varphi_i),$$

where $\Phi_{tjk}(.)$ is the appropriate cumulative distribution function whose probability distribution function is determined from Equation 15. Note that this is a 2J + 2 dimensional integral. Therefore, the probability of consumer (household) i making the sequence of purchases given by D_{mijt}, m = 1, 2, j = 0, 1, …, J, t = 1, …, T_i, conditional on θ and φ_i, is

$$(17) \quad \text{Prob}_i(\theta, \varphi_i) = \prod_{t=1}^{T}\sum_{j=0}^{J}\sum_{k=0}^{J} D_{1ijt}D_{2ijt}\Phi_{tjk}(\theta, \varphi_i).$$

Integrating over φ_i, we obtain

$$(18) \quad \text{Prob}_i(\theta) = \int_{\Omega} \text{Prob}(\theta, \varphi_i) f(\varphi_i|\theta) d\varphi_i,$$

where Ω is the domain of the integration, whereas $f(\varphi_i|\theta)$ is the multinomial probability distribution function for φ_i, conditional on θ.

Thus, we estimate a multivariate multinomial probit model, which has been adopted in some recent articles in marketing as well (e.g., Manchanda, Ansari, and Gupta 1999). This model allows random components to be correlated across the m categories, which Manchanda, Ansari, and Gupta label as “co-incidence.” Thus, factors that are unobserved by the analyst but known by the consumer could be correlated across categories. However, for the first time in the economics and marketing literature, we also incorporate into this model a process by which the variance of the random component (as well as the covariance of this component across the m categories) is updated over time, on the basis of past purchases of the consumers and past advertisement. The extent of the updating is determined by $1/\sigma^2_{\delta m}$ in the case of use experience and by $1/\sigma^2_{\eta m}$ in the case of advertising; that is, the more precise the information source is, the more updating there will be.

Given Equation 18, the log-likelihood function to be maximized is

$$\text{LogL}(\theta) = \sum_{i=1}^{I} \ln[\text{Prob}_i(\theta)], \quad (19)$$

Note that the calculation of $\text{Prob}_i(\theta)$ in Equation 19 requires the evaluation of multiple integrals, which in turn requires Monte Carlo simulation techniques. We use a probability simulator as the Monte Carlo method (Geweke 1991; Hajivassiliou, McFadden, and Ruud 1994; Keane 1990, 1994). As our estimation method, we adopt the method of simulated moments (MSM) first developed by McFadden (1989) and extended by Keane (1990).

EMPIRICAL ANALYSIS

Data

The models are estimated on scanner panel data provided by ACNielsen for toothpaste and toothbrushes. Given new product feature introductions and the existence of long-term experience attributes (e.g., cavity-fighting power of a toothpaste), quality uncertainty may exist even in the relatively mature product categories typically studied in scanner panel research (Erdem and Keane 1996). Also note that because most frequently purchased product categories are not high-involvement goods, consumers typically rely more on brand names and advertising than on active search to resolve any quality uncertainty.

The panels cover 157 weeks from the end of 1991 to the end of 1994. The data sets include households from two test markets in Chicago and Atlanta. We use the Chicago panel for model calibration. We use the Atlanta panel to assess out-of-sample fit (i.e., the predictive validity of the models). The analysis includes four brands in each category. In both the calibration (Chicago) and the prediction (Atlanta) panel, we randomly draw the panel members from the sample of households that do not buy multiple brands in a given category on the same purchase occasion.

The first two brands (Brand 1 and Brand 2) are available in both categories. Table 1 provides summary statistics. The weekly GRPs are plotted in Figure 1. The price used in the study is the price paid without any coupons. Using a price value net of coupons introduces a serious endogeneity problem; therefore, we model coupon effects by using the coupon availability measure we have defined previously.

Parameter Estimates and Goodness of Fit

We estimated the model described previously and various nested models. Table 2 reports the results for five nested models and the full model. The sixth nested model has the multivariate probit specification with correlated errors and allows for updating errors on the basis of past purchases but does not allow the errors to be updated on the basis of past advertising. The fourth nested model (NM4) has the multivariate multinomial probit specification with correlated errors across the categories but does not allow for updating errors on the basis of purchases and advertising. The third nested model (NM3) allows for neither updating nor correlated errors across the two categories. The second nested model (NM2) is similar to NM3 but does not allow for use experience, price, coupon availability, advertising, display, and feature in one category to affect the utility of the other category. Finally, the first nested model (NM1) is similar to NM2 except that heterogeneity distributions are assumed to be independent across the two categories. Both in-sample and out-of-sample, the full model fits the data statistically better than all other nested models. Therefore, we focus on the parameter estimates obtained by estimating the full model.

In a given category, the results indicate that coupon availability, advertising, displays, features, and use experience all have significant, positive effects on consumer utility, whereas price has the expected negative effect. There is significant heterogeneity in consumer tastes and responses to use experience and marketing-mix variables. The time trend in the no-purchase specification is statistically insignificant.

Given the objectives of this article, the important parameter estimates are associated with the cross-effects of marketing-mix variables (and use experience), as well as the cross-category parameters that govern the process of updating the utility error term variance over time through use experience and advertising. These parameter estimates are marked in bold in Table 3.

We find that use experience in one category has a positive impact on brand choice probabilities in the other category

Table 1
SUMMARY STATISTICS

Brand Name	*Market Share*	*Average Price*[a]	*Average GRP*	*Frequency of Display*	*Frequency of Feature*	*Average Coupon*[b]
Toothpaste						
Brand 1	31.3%	$1.81	13.54	2.0%	2.9%	$.15
Brand 2	20.0%	$1.87	27.07	1.6%	2.8%	$.18
Brand 3	10.6%	$1.81	0	1.4%	3.2%	$.23
Brand 4	9.5% (71.4%)	$2.67	0	1.2%	1.8%	$.23
Toothbrush						
Brand 1	10.2%	$2.36	12.62	1.2%	2.6%	$.23
Brand 2	21.8%	$1.99	19.75	1.1%	3.1%	$.19
Brand 5	19.4%	$2.36	22.84	.6%	3.2%	$.27
Brand 6	17.3% (68.7%)	$1.96	0	.7%	3.3%	$.19

[a]Weighted average price per 50 ounces for toothpaste. Weighted average price per unit for toothbrush.
[b]Average nonzero coupon value of toothpaste normalized at 50 ounces. Average nonzero coupon value of toothbrush per unit.

Figure 1

WEEKLY GRPs

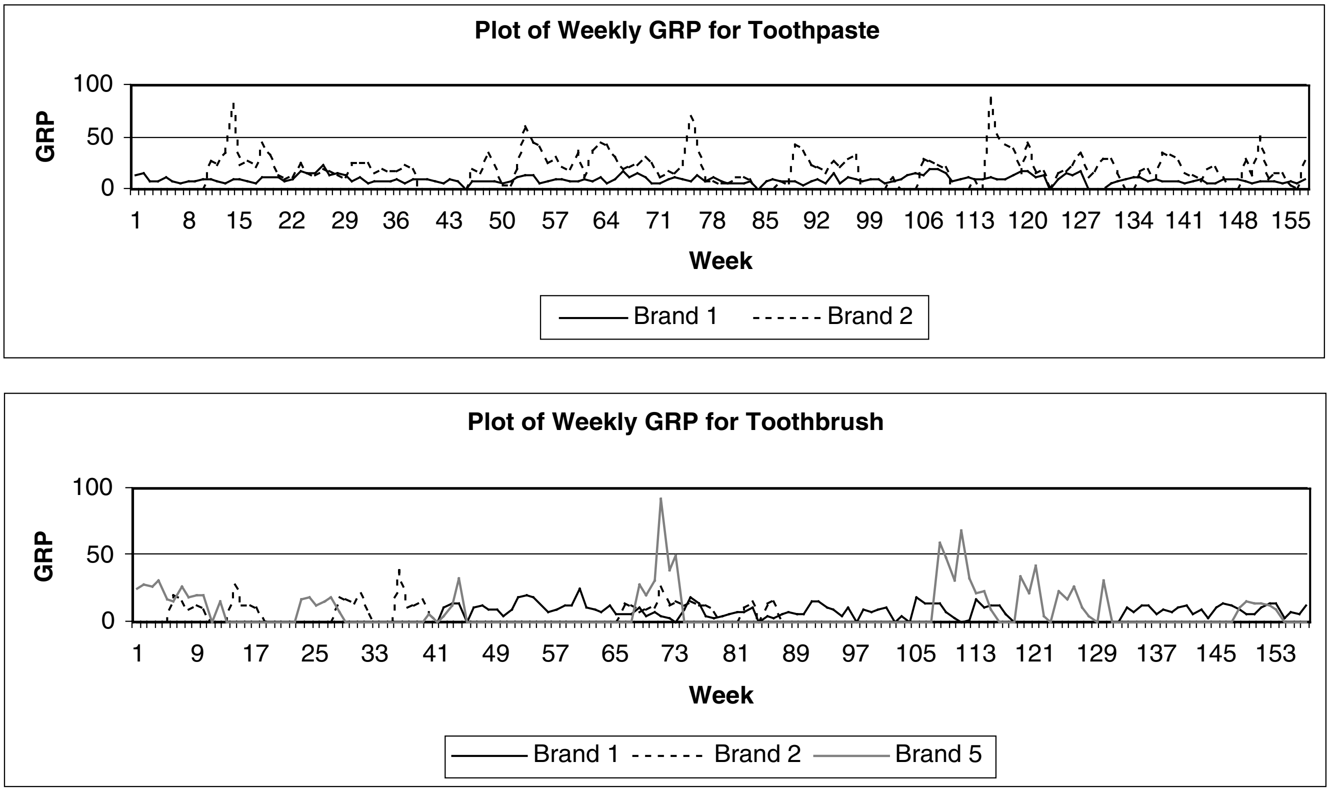

Table 2

MODEL SELECTION

	NM1	*NM2*	*NM3*	*NM4*	*NM5*	*FM*
In-Sample (Chicago)[a]						
–LL	21323.4	20731.6	20212.5	20101.2	19510.4	18925.3
AIC	21417.4	20831.6	20336.5	20226.2	19637.4	19054.3
Out-of-Sample (Atlanta)[b]						
BIC	21839.0	21280.1	20892.3	20786.9	20208.0	19633.9
–LL	13260.5	12936.2	12712.2	12592.7	12367.5	12179.6

[a]Number of observations = 59,032 (including no purchases), number of households (hhs) = 376; 167 hhs made 621 purchases of toothbrush; 345 hhs made 2880 purchases of toothpaste; 136 hhs purchased both toothbrush and toothpaste.

[b]Number of observations = 30,301 (including no purchases), number of hhs = 193; 92 hhs made 198 purchases of toothbrush; 186 hhs made 912 purchases of toothpaste; 85 hhs purchased both toothbrush and toothpaste.

Notes: LL = log likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion.

for umbrella brands. We also find statistically significant cross-category effects of advertising in both categories. Furthermore, we find evidence that coupon availability and display (significant at the $p < .10$ level) in the toothbrush category affects consumer utility in toothpaste positively for umbrella brands. Coupon availability, display, and feature in the toothpaste category affect consumer utility in the toothbrush category positively as well. Finally, prices have negative cross-category effects in both categories. Therefore, a price cut in one category for an umbrella brand increases consumer utilities and thus the choice probabilities for that brand in the other category.

Turning our attention to the random component of the consumer utility and the process of utility variance updating based on use experience and advertising, we find the following results: Random components are correlated across the two categories. Recall that we estimated an initial correlation between the random components, which we find to be positive and significant. However, our results indicate that both $\sigma_{\delta m}$ and $\sigma_{\eta m}$ are statistically significant in both categories. Therefore, depending on the degree of the precision of information (i.e., $1/\sigma_{\delta m}$ or $1/\sigma_{\eta m}$), the variance and covariance of random components across the two categories are updated with use experience and advertising. This result

Table 3
MODEL ESTIMATION

Parameters		*Toothpaste (m = 1)*	*Toothbrush (m = 2)*
Brand specific constants α_{mj}	Brand 1	–2.07(.19)	–3.77(.32)
	Brand 2	–2.54(.28)	–.26(.10)
	Brand 3 (5)[a]	–3.29(.22)	–.86(.21)
	Brand 4 (6)	–3.31(.17)	–1.03(.26)
	No purchase[b]	0	0
Standard deviation of brand specific constant $\sigma_{\alpha mj}$	Brand 1	1.51(.34)	1.02(.18)
	Brand 2	1.35(.20)	.47(.19)
	Brand 3 (5)	1.00(.22)	.23(.11)
	Brand 4 (6)	.58(.11)	.11(.07)
	No purchase	0	0
Trend$_m$		.015(2.53)	.002(1.10)
		.010(2.57)	.001(1.73)
Mean price coefficient β_m		–1.21(.18)	–.95(.13)
Standard deviation of the price random effect $\sigma_{\beta m}$		.56(.16)	.45(.12)
Mean coupon coefficient θ_m		.82(.12)	.95(.17)
Standard deviation of the coupon random effect $\sigma_{\theta m}$		.55(.16)	.46(.20)
Mean ad coefficient γ_m		.12(.05)	.15(.05)
Standard deviation of the ad random effect $\sigma_{\vartheta m}$		.05(.02)	.07(.04)
Mean display coefficient λ_m		1.49(.26)	1.36(.33)
Standard deviation of the display random effect $\sigma_{\lambda m}$		1.20(.25)	.75(.23)
Mean feature coefficient τ_m		1.09(.40)	1.29(.20)
Standard deviation of the feature random effect $\sigma_{\tau m}$		.82(.43)	.43(.59)
Mean use experience coefficient κ_m		2.74(.33)	2.10(.23)
Standard deviation of the use experience random effect $\sigma_{\kappa m}$		1.86(.30)	1.10(.23)
Mean cross-price coefficient ξ_{3-m}		**–.11(.04)**	**–.18(.08)**
Standard deviation of the cross-price random effect $\sigma_{\xi 3-m}$		**.08(.13)**	**.08(.08)**
Mean cross-coupon coefficient ζ_{3-m}		**.45(.18)**	**.47(.17)**
Standard deviation of the cross-coupon random effect $\sigma_{\zeta 3-m}$		**.23(.09)**	**.20(.08)**
Mean cross-ad coefficient ι_{3-m}		**.011(.005)**	**.013(.005)**
Standard deviation of the cross-ad random effect $\sigma_{\iota 3-m}$		**.008(.005)**	**.011(.004)**
Mean cross-display coefficient μ_{3-m}		**.097(.055)**	**.147(.077)**
Standard deviation of the cross-display random effect $\sigma_{\mu 3-m}$		**.091(2.58)**	**.100(1.15)**
Mean cross-feature coefficient ν_{3-m}		**.132(.083)**	**.170(.037)**
Standard deviation of the cross-feature random effect $\sigma_{\nu 3-m}$		**.085(.044)**	**.095(.144)**
Mean cross-use experience coefficient ω_{3-m}		**.82(.25)**	**.69(.14)**
Standard deviation of the cross-use experience random effect $\sigma_{\omega 3-m}$		**.45(.45)**	**.20(.09)**
Use experience smoothing parameter DU$_m$		.78(.12)	.88(.25)
Media smoothing parameter DA$_m$		.28(.10)	.56(.17)
Correlation between constant terms and price $\rho_{\alpha m \beta m}$	Brand 1	.15(.09)	.13(.08)
	Brand 2	.19(.19)	.17(.06)
	Brand 3 (5)	.07(.11)	–.08(.09)
	Brand 4 (6)	–.29(.05)	–.25(.11)
Correlation between constant terms and advertising $\rho_{\alpha m \gamma m}$	Brand 1	.12(.04)	.14(.05)
	Brand 2	.09(.05)	.15(.07)
	Brand 3 (5)	.06(.03)	.08(.06)
	Brand 4 (6)	.07(.05)	.07(.05)
Correlation between price and ad coefficients $\rho_{\beta m \gamma m}$		–.17(.08)	.16(.06)
Correlation between price and display coefficients $\rho_{\beta m \lambda m}$		–.25(.10)	–.23(.11)
Correlation between price and feature coefficients $\rho_{\beta m \tau m}$		–.17(.07)	–.22(.10)
Correlation between price and coupon coefficient $\rho_{\beta m \theta m}$		–.18(.07)	–.13(.07)
Correlation between price and use experience coefficients $\rho_{\beta m \kappa m}$		–.21(.09)	–.20(.11)
Correlation between ad and display coefficients $\rho_{\gamma m \lambda m}$		.11(.06)	–.18(.08)
Correlation between ad and feature coefficients $\rho_{\gamma m \tau m}$		.08(.04)	.13(.05)
Correlation between ad and coupon coefficients $\rho_{\gamma m \theta m}$		.16(.07)	.10(.09)
Correlation between ad and use experience coefficients $\rho_{\gamma m \kappa m}$		.27(.12)	.23(.13)
Cross-category correlation between price coefficients $\Lambda_{\beta 1 \beta 2}$			.63(.13)
Cross-category correlation between ad coefficients $\Lambda_{\gamma 1 \gamma 2}$			.44(.10)
Cross-category correlation between display coefficients $\Lambda_{\lambda 1 \lambda 2}$			.16(.10)
Cross-category correlation between feature coefficients $\Lambda_{\tau 1 \tau 2}$			.13(.08)
Cross-category correlation between coupon coefficients $\Lambda_{\theta 1 \theta 2}$			.14(.10)
Cross-category correlation between use experience coefficients $\Lambda_{\kappa 1 \kappa 2}$			.42(.18)
Cross-category correlation between error terms ρ (in the initial period)			.19(.08)
Advertising variability σ_δ for toothbrush			.22(.11)
Advertising variability σ_δ for toothpaste			.74(.31)
Experience variability σ_η for toothbrush			**.16(.06)**
Experience variability σ_η for toothpaste			.27(.11)

[a]Toothpaste brands are 1, 2, 3, and 4, and toothbrush brands are 1, 2, 5, and 6.
[b]No-purchase option constant is set to zero for identification purposes.
Notes: Figures in boldface indicate parameter estimates associated with the cross-effects of marketing-mix variables and the cross-category parameters that govern the process of updating the utility error term variance over time.

confirms the finding in the literature that use experience may reduce uncertainty across categories for umbrella brands (Erdem 1998) and establishes the new result that advertising decreases consumer uncertainty across product categories for umbrella brands as well.

Note also that the precision of use experience information is found to be higher than that of advertising in both categories, which is an intuitive result because use experience should provide less noisy information than advertising does in most cases. Also, the ratio of advertising variability to use experience variability is higher for toothpaste than toothbrushes; that is, although advertising provides more noisy information than does use experience in both categories, the relative noisiness of advertising information is greater for toothpaste than toothbrushes.

Finally, we estimated several within-category as well as across-category correlations, as discussed in the previous section. Not all the correlations between brand constants and price (advertising) responses are statistically significant. The statistically significant estimates suggest that in the toothpaste (toothbrush) category, consumers who like Brand 1 (Brand 2) more than the average consumer tend to be less price sensitive than the average consumer. The reverse is true for Brand 4. Therefore, the correlation between brand specific constants and price sensitivity is positive for some brands and negative for others. The estimates also suggest that consumers who like Brands 1, 2, and 3 in toothpaste and Brands 1 and 2 in toothbrushes more than the average consumer tend to be more advertising sensitive than the average consumer. Finally, in both categories, there are statistically significant correlations of price sensitivity with advertising, display, feature, and use experience sensitivities. Advertising and feature sensitivities and advertising and display sensitivities are significantly correlated in both categories as well. Advertising and coupon availability sensitivities, as well as advertising and use experience sensitivities, are significantly correlated only in the toothpaste category.

Given the signs of the parameter estimates, these combined results indicate that in the two categories we study, there seems to be an individual-specific trait we call "marketing-mix sensitivity" (i.e., some consumers are in general more sensitive to marketing-mix strategies). Indeed, similar results have been found in other recent work as well (Arora 2000). The only result that seems somewhat surprising is the negative sign of the correlation between use experience and price sensitivities. Although these correlation terms do not necessarily imply any causal links, we might still have expected the reverse result to hold. This is because high use experience involves positive purchase feedback, and consumers who are sensitive to this may be expected to be less price sensitive (Seetharaman, Ainslie, and Chintagunta 1999). However, note that the estimate we obtain is not necessarily counterintuitive. This is because more use experience–sensitive people may have utility farther out in the tail of the distribution and may need a larger price coefficient to have the same price elasticity. This would be consistent with high sensitivity to use experience being associated with high price sensitivity. Another explanation for the result is that consumers with higher sensitivity to use experience may have smaller consideration sets (Rajendran and Tellis 1994); this may increase the ability of use experience–sensitive consumers to make price comparisons, which may result in higher price sensitivities in these two categories, ceteris paribus. Finally, we also find that consumer price, advertising, and use experience sensitivities are correlated across the two categories we study.

Policy Simulations

To evaluate the impact of temporary policy changes (i.e., a change in one of the marketing-mix elements in the second week) in each category, we ran the following simulations separately for Brand 1 and Brand 2: a 20% increase in (1) coupon availability, (2) advertising, (3) displays, and (4) features and (5) a 20% decrease in price. We report only the impact of the policy change on the cumulative purchases. The impact of the temporary change on cumulative sales can be conceptualized as the long-term effect of these temporary policy changes. In regard to the short-term effects of a temporary policy change (i.e., the impact of a policy change in the beginning of the second week on sales in that week), it may suffice to indicate that the short-term effects are larger. It is also worthwhile to note that we found the long-term effects to be larger than the short-term effects in advertising.

Table 4 reports the results for the respective temporary policy changes adopted by Brand 1 in toothpaste and toothbrushes separately. Table 5 reports the corresponding results for Brand 2. In both Tables 4 and 5, the first half of the table compares the baseline figures with the cumulative "sales" figures when a temporary policy change was adopted in Week 2 (or just before Week 2 in the case of advertising and coupon availability). In particular, the first row indicates the baseline figures. The next five rows indicate the impacts of a change in pricing, couponing, advertising, display, and feature policy, respectively, in toothbrush on toothpaste and toothbrush sales. The following five rows reveal the impacts of a change in pricing, couponing, advertising, display, and feature policy, respectively, in toothpaste on toothpaste and toothbrush sales. The lower half of the table reports the percentage change in sales due to the respective policy changes, again separately for toothbrushes and toothpaste. The tables do not include the feature effects in toothpaste, because the cross-effects of features were found to be statistically insignificant for toothpaste.

To assess the impact of a 20% increase in Brand 1's advertising frequency in toothbrushes on the toothpaste sales of Brand 1, for example, compare the baseline figure of 1326, which reflects the baseline cumulative sales of Brand 1, with the corresponding postintervention (a temporary increase in advertising frequency by Brand 1 in toothbrushes at Purchase Occasion 2) figure of 1431. This comparison reveals an 8% increase in toothpaste sales due to a 20% increase of advertising frequency of Brand 1 in the toothbrush category.

The results on spillover effects (cross-effects) can be summarized as follows: Overall, coupons and then advertising have the largest cross-effects on sales in both categories except for Brand 2 in the toothpaste category, for which features (more so than any other marketing-mix element in the toothpaste category) affect sales the most in the toothbrush category, followed by coupons and advertising. In most cases, the smallest cross-effects are the price cross-effects. The cross-effects of coupon availability on sales range from 5% to 13% across product categories and across Brand 1 and Brand 2. The advertising cross-effects range from 4% to 8%.

Table 4

SIMULATION RESULTS FOR POLICY CHANGES BY BRAND 1

	Sales of Toothpaste				*Sales of Toothbrush*			
	Brand 1	*Brand 2*	*Brand 3*	*Brand 4*	*Brand 1*	*Brand 2*	*Brand 5*	*Brand 6*
Baseline	1326	777	424	353	99	256	160	106
Toothbrush								
Price cut by 20%	**1405**	734	402	339	*121*	245	154	101
Coupon increase by 20%	**1464**	713	384	319	*118*	245	155	103
Advertising increase by 20%	**1431**	734	388	327	*125*	141	153	102
Display increase by 20%	**1419**	730	397	334	*124*	243	152	102
Feature increase by 20%					*116*	246	155	104
Toothpaste								
Price cut by 20%	*1748*	519	334	279	**105**	252	159	105
Coupon increase by 20%	*1763*	571	299	255	**112**	248	158	103
Advertising increase by 20%	*1665*	594	338	283	**107**	252	157	105
Display increase by 20%	*1659*	600	340	281	**105**	253	159	104
Feature increase by 20%	*1641*	604	343	292	**104**	255	158	104

	Toothpaste				*Toothbrush*			
	Brand 1	*Brand 2*	*Brand 3*	*Brand 4*	*Brand 1*	*Brand 2*	*Brand 5*	*Brand 6*
Toothbrush								
Price cut by 20%	**.0596**	–.055	–.052	–.04	*.2222*	–.043	–.038	–.047
Coupon increase by 20%	**.1041**	–.082	–.094	–.096	*.1919*	–.043	–.031	–.028
Advertising increase by 20%	**.0792**	–.055	–.085	–.074	*.2626*	–.449	–.044	–.038
Display increase by 20%	**.0701**	–.06	–.064	–.054	*.2525*	–.051	–.05	–.038
Feature increase by 20%					*.1717*	–.039	–.031	–.019
Toothpaste								
Price cut by 20%	*.3183*	–.332	–.212	–.21	**.0606**	–.016	–.006	–.009
Coupon increase by 20%	*.3296*	–.265	–.295	–.278	**.1313**	–.031	–.013	–.028
Advertising increase by 20%	*.2557*	–.236	–.203	–.198	**.0808**	–.016	–.019	–.009
Display increase by 20%	*.2511*	–.228	–.198	–.204	**.0606**	–.012	–.006	–.019
Feature increase by 20%	*.2376*	–.223	–.191	–.173	**.0505**	–.004	–.013	–.019

Notes: The cross-effects are indicated in bold and the own-effects are indicated in italics. The figures in bold and italics refer to the impacts of the policy changes on the sales of the umbrella brand implementing the policy change.

The display cross-effects range from 3% to 7%. Similarly, the feature cross-effects in toothbrush (the impact of a change in the display activity in toothpaste on toothbrush sales) are 5% for both Brands 1 and 2. Finally, price cross-effects range from 3% to 6% as well in both categories.

The simulation results for a temporary policy change by Brand 1 (Brand 2) in the toothbrush category suggest that as a percentage of the own-effects, cross-effects on Brand 1's (Brand 2's) toothpaste sales are 27%, 54%, 30%, and 28% (23%, 61%, 43%, and 64%) for price, coupon availability, advertising, and display, respectively. Thus, in the toothpaste category, coupon availability and then advertising have the largest cross-effects as a percentage of own-effects for Brand 1, and displays and coupons have the largest cross-effects as a percentage of own-effects for Brand 2. The simulation results for a temporary policy change by Brand 1 (Brand 2) in the toothpaste category suggest that as a percentage of the own-effects, cross-effects on Brand 1's (Brand 2's) toothbrush sales are 19%, 40%, 32%, 24%, and 21% (16%, 61%, 43%, 64%, and 29%) for price, coupon availability, advertising, display, and feature, respectively. Thus, in the toothbrush category, as in the toothpaste category, cross-effects as a percentage of own-effects are largest for coupons and advertising for Brand 1. For Brand 2, in the toothbrush category, cross-effects as a percentage of own-effects are largest for features, because of a policy change in the toothpaste category, followed by coupons and advertising. In contrast, in the toothpaste category these effects are largest for display and coupons, followed by advertising. As these numbers show, as a percentage of own-effects, cross-effects are substantial for all marketing-mix elements.

MANAGERIAL IMPLICATIONS, CONCLUSIONS, AND FURTHER RESEARCH

We tested for the spillover effects of advertising and other marketing-mix/sales promotion strategies (price, coupon, display, and feature) in umbrella branding on scanner panel data. We found that advertising spillover effects, along with the use experience spillover effects, affect both utility mean and variance. The latter effect provides evidence for the uncertainty-reducing role of advertising (along with use experience) across categories for umbrella brands. To capture the variance effect in a parsimonious way, for the first time in the literature, we estimated a multivariate multinomial probit model, in which the variances and covariances of random components of utilities across categories were updated on the basis of use experience and advertising.

Although there were some differences across categories and brands, marketing-mix spillover effects were largest for coupon availability, generally followed by advertising. The relatively large coupon effects, as well as advertising effects, can be explained by various behavioral phenomena related to brand equity; for example, couponing or advertising by an umbrella brand may increase consumer awareness of prod-

Table 5

SIMULATION RESULTS FOR POLICY CHANGES BY BRAND 2

	Sales of Toothpaste				*Sales of Toothbrush*			
	Brand 1	*Brand 2*	*Brand 3*	*Brand 4*	*Brand 1*	*Brand 2*	*Brand 5*	*Brand 6*
Baseline	1326	777	424	353	99	256	160	106
Toothbrush								
Price cut by 20%	1294	**813**	419	354	85	*307*	140	89
Coupon increase by 20%	1270	**867**	403	340	84	*305*	142	90
Advertising increase by 20%	1306	**829**	404	341	85	*296*	146	94
Display increase by 20%	1311	**814**	410	345	95	*275*	152	99
Feature increase by 20%					96	*271*	153	101
Toothpaste								
Price cut by 20%	1206	*966*	382	326	95	**266**	157	103
Coupon increase by 20%	1207	*963*	383	327	94	**269**	156	102
Advertising increase by 20%	1226	*950*	385	319	94	**267**	158	102
Display increase by 20%	1237	*924*	392	327	95	**264**	158	104
Feature increase by 20%	1246	*915*	390	329	93	**269**	157	102

	Toothpaste				*Toothbrush*			
	Brand 1	*Brand 2*	*Brand 3*	*Brand 4*	*Brand 1*	*Brand 2*	*Brand 5*	*Brand 6*
Toothbrush								
Price cut by 20%	–.024	**.0463**	–.012	.0028	–.141	*.1992*	–.125	–.16
Coupon increase by 20%	–.042	**.1158**	–.05	–.037	–.152	*.1914*	–.113	–.151
Advertising increase by 20%	–.015	**.0669**	–.047	–.034	–.141	*.1563*	–.088	–.113
Display increase by 20%	–.011	**.0476**	–.033	–.023	–.04	*.0742*	–.05	–.066
Feature increase by 20%					–.03	*.0586*	–.044	–.047
Toothpaste								
Price cut by 20%	–.09	*.2432*	–.099	–.076	–.04	**.0391**	–.019	–.028
Coupon increase by 20%	–.09	*.2394*	–.097	–.074	–.051	**.0508**	–.025	–.038
Advertising increase by 20%	–.075	*.2227*	–.092	–.096	–.051	**.043**	–.013	–.038
Display increase by 20%	–.067	*.1892*	–.075	–.074	–.04	**.0313**	–.013	–.019
Feature increase by 20%	–.06	*.1776*	–.08	–.068	–.061	**.0508**	–.019	–.038

Notes: The cross-effects are indicated in bold and the own-effects are indicated in italics. The figures in bold and italics refer to the impacts of the policy changes on the sales of the umbrella brand implementing the policy change.

ucts that share the same umbrella brand (Aaker 1991) and may strengthen the brand image (Keller 1993). Given that clipping the coupons and using them requires more cognitive elaboration on the part of consumers, such cross-effects may even be larger for coupons than for advertising, as our results indicate.

We also found that advertising (as well as use experience) shifts both utility mean and variance across categories. Thus, we found that the variance of the random component of utility in each category declined as a result of advertising (and use experience) in either category over time. The cross-category effects of advertising on the utility mean may be due to the factors discussed previously, such as awareness, as well as advertising's effect of increasing quality beliefs under uncertainty. However, the effect of advertising on utility variance is evidence for learning due to advertising under uncertainty (the variance of quality beliefs is decreasing over time because of advertising). Thus, we find evidence for the uncertainty-reducing role of advertising across categories, which gives rise to advertising spillover effects, though the effects on mean utility may be a combination of different impacts (related or not related to uncertainty).

Our empirical results obtained from the analysis of revealed preference data have several other managerial implications. First, the results confirm the expectation that umbrella branding generates savings in brand development and marketing costs over time and enhances marketing productivity. These results call for integrated marketing communications across products that share the same brand name. Work on brand equity suggests this for advertising, but our results suggest that the need for integration exists for all the marketing-mix elements, including sales promotions and especially couponing strategies, given the relatively large cross-couponing effects we found.

Second, our results imply that there are some asymmetries across product categories and across brands. For example, for Brand 2, featuring toothpaste will have the largest cross-effects on toothbrush sales, whereas displaying the toothbrush product (or giving a coupon for it) will have the largest cross-effects on toothpaste sales, ceteris paribus. Furthermore, as a percentage of own-effects, cross-effects of a policy change in toothbrush seem to affect toothpaste sales more than the other way around in the case of Brand 2, whereas the magnitudes of cross-effects as a percentage of own-effects are fairly similar across the two categories for Brand 1. Therefore, it would be important for brand managers to know how specific cross-effects work across categories for their brands.

Although it was not the focus of this article, we also estimated and found evidence for several within- and cross-category correlations in response coefficients. First, we found that marketing-mix sensitivities are generally positively correlated within a category. We also found that depending on the brand in question, some consumers who like certain brands may be more or less price sensitive than the average consumer. These results indicate that in these two categories, there are segments that, overall, are marketing-mix sensitive, as well as segments that are marketing-mix insensitive. Second, the finding that consumers' marketing-mix sensitivities tend to be correlated across categories suggests that there is a strong individual-specific component to marketing-mix sensitivity.

There are a few avenues for further research. We showed evidence for both utility mean– and utility variance–shifting effects of advertising and use experience, and the the variance effects indicate evidence for the uncertainty-reducing role that advertising and use experience play across categories for umbrella brands. The processes by which these spillover effects occur are worth exploring in more detail. However, as discussed by Keane (1997a), because of identification issues that arise with respect to models estimated on panel data, it is often not feasible to differentiate among all possible behavioral processes using scanner panel data. Survey or experimental data would be needed to provide a detailed account of all the underlying behavioral processes.

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