Understanding Reference-Price Shoppers: A within- and Cross-Category Analysis
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The authors attempt to draw profiles of reference-price shoppers. Specifically, the authors study how selected factors that affect brand choice are correlated with consumer sensitivity to gains and losses with respect to internal reference prices. They also study the interaction between sociodemographics and gain and loss sensitivity. Furthermore, the authors analyze cross-category correlations in gain and loss sensitivity to shed light on their individual- and category-specific characters. In three categories, the results show significant heterogeneity in loss sensitivity among consumers and indicate that loss sensitivity is greater and more heterogeneous than gain sensitivity. Across categories, the results show that loss-sensitive shoppers are less influenced by past brand use and that both loss- and gain-sensitive shoppers more sensitive to price, display, and feature than the average consumer. Loss-sensitive households tend to be larger, and their heads are less likely to be fully employed, whereas gain-sensitive households have no clear demographic profile. The authors also discuss the limitations of latent-class models in profiling consumer segments and show how these problems are overcome using models with continuous, correlated multivariate distributions.

Understanding Reference-Price Shoppers: A Within- and Cross-Category Analysis

The phenomenon of reference price has been a popular topic in marketing research for many years. So popular, in fact, that Kalyanaram and Winer (1995) were able to describe empirical generalizations arising from the extant body of reference-price research. Despite the progress that has been made, however, marketers have little idea of who is the "reference-price shopper." There is certainly heterogeneity in consumer response to marketing-mix variables, and price recall studies (e.g., Dickson and Sawyer 1990) suggest heterogeneity in reference-price responsiveness. Indeed, recent work (e.g., Arora 2000) finds significant heterogeneity in reference-price sensitivity.

An understanding of heterogeneity in reference-price responsiveness is important to the understanding of consumer behavior. It is important to know how reference-price responsiveness varies with consumers' responsiveness to price and other marketing-mix variables and explore whether sociodemographics play any role in reference-price sensitivity. A picture of the reference-price consumer would be valuable to the marketer who makes price and promotion decisions. For example, do reference-price and non–reference-price shoppers differ in their sensitivity to use experience, promotion, and so forth? If consumers who are sensitive to reference price are also sensitive to use experience,[1] manufacturers should be concerned that consumers who buy their brands repeatedly are those who are most likely to use past price information in their brand-choice decisions. If so, price promotions may be an ineffective way of targeting other brands' loyal consumers.

In this study, we investigate the distribution of reference-price sensitivity and aim to draw a profile of the reference-price shopper. We focus on internal reference prices (IRPs; Winer 1986) and therefore define reference-price–sensitive shoppers as shoppers who take their past exposure to prices

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[1]"Use experience" (purchase feedback) refers to the impact of past purchases on current choices. It commonly has been called "brand loyalty" (Guadagni and Little 1983), but brand loyalty (a tendency to purchase a small subset of brands repeatedly) has two components: the positive impact of past purchases on current choices (positive state dependence) and a match between tastes and product offerings (taste heterogeneity). We use "brand loyalty," however, in discussing previous work that uses this term.

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into consideration when making a brand-choice decision. Consistent with previous literature on IRPs, we operationalize reference-price sensitivity as the sensitivity to the deviations of the current retail price from IRPs, which, in turn, are formed as a weighted average of item-specific past prices to which a consumer is exposed.

We profile reference-price shoppers on the basis of correlations between reference-price sensitivity and sensitivities to marketing-mix variables (price, display, and feature), as well as use-experience sensitivities. We also study the interaction between sociodemographics and reference-price sensitivity. Furthermore, we analyze cross-category correlations in reference-price sensitivity to shed some light on the individual- or category-specific character of reference-price sensitivity.

The following section is a short review of the reference-price literature. In the next section, we present hypotheses regarding the profiles of reference-price shoppers. We then discuss our model and data and present our estimation results. Previous research has employed latent-class modeling techniques (Kamakura and Russell 1989) to study characteristics of reference-price–sensitive consumers. Therefore, we compare the results of the latent-class models with those of the continuous multivariate model and discuss how modeling consumer heterogeneity with latent-class approaches causes segment membership to be determined by variables that explain most of the variance in brand-choice data (e.g., brand preferences). Finally, we discuss managerial implications and directions for further research.

LITERATURE REVIEW

Since the early 1980s, many researchers, using different econometric models (most often the logit model), have investigated the effect of reference price in consumer choice, usually with frequently purchased products. Kalyanaram and Winer (1995), drawing empirical generalizations from the body of the extant reference-price research, state that reference prices have a consistent and statistically significant impact on consumer demand. However, research has shown that most of the variance in brand-choice data can be captured by brand preferences, use experience, and price (e.g., Keane 1997). Although reference prices clearly affect brand choices, they explain less variance in choice data than the primary drivers do (e.g., Bell and Lattin 2000; Mazumdar and Papatla 1995).

The influence of reference prices on choice and the heterogeneity in reference-price sensitivity raise an important question: Who are the reference-price–sensitive consumers? Indeed, this question has motivated other researchers to investigate this issue as well. For example, Mazumdar and Papatla (2000) focus on the use of external reference prices (ERPs) versus IRPs. They investigate whether product category characteristics, such as display activity, and consumer characteristics, such as interpurchase times, are associated with the relative importance of IRPs versus ERPs. Arora (2000) also investigates the relative importance of IRPs versus ERPs, linking reference-price usage to product characteristics and sociodemographics using a hierarchical Bayes approach.[2]

[2]Chang, Siddarth, and Weinberg (1999) also investigate IRP, using a multistage hierarchical Bayes model of purchase incidence and brand choice. This method yields a Bayesian posterior distribution of covariance, but the authors do not investigate correlates of reference-price effects.

Both articles provide some initial understanding of which factors may affect reference-price usage, but they do not go so far as to profile reference-price shoppers. For example, Mazumdar and Papatla (2000) estimate a latent-class model in which IRP and ERP sensitivities are constrained to sum to one. Then, they explore whether the estimated IRP–ERP parameter shows a pattern across segments vis-à-vis percentage of purchases associated with a display, feature, and so on. Although this type of analysis is useful, it is exploratory and does not yield any statistically verifiable relationships. It would be helpful to see segment-level estimates in judging whether segments with larger price coefficients tend to use more IRPs than ERPs. However, conclusive statements are impossible, because latent-class approaches do not provide estimates of correlations among consumer sensitivities; therefore, statistical inference cannot be made. Furthermore, latent-class models face serious problems in classifying consumers into different segments on the basis of secondary drivers of choice such as reference prices and sociodemographics (DeSarbo et al. 1997), as we discuss subsequently. Arora (2000), using scanner-panel data, investigates whether sociodemographics correlate with loss aversion in (reference) prices but does not investigate the relationship between other consumer marketing-mix sensitivities and reference-price sensitivity. Although both studies estimate the models on multiple categories, neither analyzes cross-category correlations. Thus, they do not analyze whether a consumer who is reference-price–sensitive in one category tends to be so in other categories as well.

Han, Gupta, and Lehmann (1993) provide interesting characteristics of reference-price–sensitive shoppers in a model of gain and loss thresholds, in accordance with assimilation–contrast theory (Monroe 1973; Sherif and Hovland 1961; Winer 1988). They model gain and loss thresholds as functions of marketing activity, income, and deal proneness, and they cluster the households ex post on the basis of threshold sizes. They find that consumers with low thresholds for gain and loss (i.e., high sensitivity to gains and losses) are more deal-prone, less loyal to a single store, better educated, and less likely to hold full-time jobs. They find exactly the opposite results for consumers with large gain and loss thresholds. Unfortunately, the results cannot be tested for statistical significance.

PROFILING REFERENCE-PRICE SHOPPERS: CONCEPTUAL ISSUES AND HYPOTHESES

As have most reference-price researchers, we operationalize reference-price effects using separate variables to account for gains and losses. This is in keeping with prospect theory (Kahneman and Tversky 1979) and mental accounting (Thaler 1985), which predict that consumers will react asymmetrically to discrepancies depending on how the discrepancies are framed relative to reference price and that consumers will show greater sensitivity in the domain of losses. Kalyanaram and Winer (1995) find this asymmetry to be one of the empirical generalizations of reference-price research. With such empirical support, researchers might be tempted to view gain and loss sensitivity as a single phenomenon and view reference-price shoppers as those with greater sensitivity in both domains. There is no evidence, however, that the sensitivities are correlated, and some research suggests they are relatively uncorrelated. Han, Gupta, and Lehmann (1993) find that higher price volatility seems to sensitize consumers to losses, whereas discount activity by other brands sensitized consumers to gains. We frame all our hypotheses as dual gain/loss hypotheses and test for correlation between gain and loss sensitivity.

The roles in consumer choice of gains and losses relative to IRPs are directly related to memory of past price perceptions; recall ability is a function of the degree of cognitive elaboration involved in processing price information (Wakefield and Inman 1993), and involvement with the task is a primary mediator of cognitive processing (Petty and Cacioppo 1986). We offer hypotheses regarding the relationship between sensitivities to gain and loss and to marketing mix and use experience, as well as the impact of sociodemographics. The hypotheses are based on the likelihood that marketing mix and other factors will increase cognitive elaboration of price information.

H_1: (a) Loss- and (b) gain-sensitive consumers are more price-sensitive than the average consumer.

Greater price sensitivity, whether it arises from tighter budget constraints, perceptions that brands are undifferentiated, or more involvement with the task of shopping, should lead to more motivation to attend to prices, greater cognitive elaboration, and subsequent ability to recall price perceptions better. This should increase sensitivity to both losses and gains. Bell and Bucklin (1995, 1999) offer limited evidence for a positive correlation between price and reference-price sensitivities. Although Murthi and Srinivasan (1999) do not specifically address reference prices, they find that consumers who are actively evaluating products use more past purchase information.

H_2: (a) Loss- and (b) gain-sensitive consumers are more display-sensitive than the average consumer.

H_3: (a) Loss- and (b) gain-sensitive consumers are more feature-sensitive than the average consumer.

If loss- and gain-sensitive consumers are indeed more price-sensitive, more reference-price–sensitive consumers may be more sensitive to price deals in general. Newspaper feature advertising and in-store displays are generally associated with price cuts, so the effects would work hand in hand. The greater attention drawn by a display or feature, together with its price-cut signal effect, increase the likelihood of the item being considered, thereby increasing the likelihood of cognitive processing of the item's attributes, including price. The price-cut signal may also draw more attention to price as an attribute to be actively processed in making the brand choice. This is consistent with Han, Gupta, and Lehmann's (1993) result that price volatility narrows the latitude of acceptance around the reference price. Shankar and Krishnamurthi (1996) find that features and feature–display combinations are associated with greater price sensitivity, though displays alone are not statistically significant.

In a special case, consumers who use past prices to make price judgments might be less persuaded by in-store promotional signals, ceteris paribus. In an experimental study, Inman, McAlister, and Hoyer (1990) find that displays may be effective without price cuts if they are associated with price cuts often enough to be seen as price-cut signals. A loss- or gain-sensitive consumer's stronger memory of price perceptions could make him or her less susceptible to the price-cut signal in the promotion. Such an effect would be secondary, however, because it would appear only in those cases in which a display or feature is not accompanied by a price cut, and thus it should not affect the sign of the correlation between loss and gain sensitivities and those of display and feature. In short, although there may be counteracting processes, the close empirical association of displays and features with price cuts suggests that H_2 and H_3 will hold.

H_4: (a) Loss- and (b) gain-sensitive consumers are less use-experience–sensitive than the average consumer.

If use experience increases consumer utility, this may imply that consumers are either persistent in their habits (Erdem 1996) or sensitive to the familiarity and low perceived risk associated with a brand (Erdem and Keane 1996), both of which lead to loyalty. Sensitivity to such behavioral processes may imply less price and reference-price (gain or loss) sensitivity, because such consumers may have lower motivation for price processing. Use experience also is associated with brand differentiation, which is associated with less sensitivity to prices in general, as well as smaller consideration sets, ceteris paribus (Rajendran and Tellis 1994). Smaller consideration sets may increase the ability of consumers to make price comparisons over time; however, choosing among fewer brands eases the cognitive burden, so it may decrease cognitive elaboration, especially in choices of inexpensive, frequently purchased products. LeBoutillier, LeBoutillier, and Neslin (1994), for example, find directional but statistically insignificant evidence of lower accuracy in price memory in more brand-loyal customers. In short, use-experience–sensitive (e.g., loyal) consumers may be driven more by the utility of their preferred brand (acquisition utility) than by the loss or gain associated with its purchase (transaction utility) (Krishnamurthi, Mazumdar, and Raj 1992); therefore, we expect H_4 to hold.

H_5: Sensitivities to (a) losses and (b) gains are correlated across categories.

Urbany, Dickson, and Kalapurakal (1996) find that habit is a significant predictor of price search behavior. If this is a general rather than product-specific habit, similar effects might be expected for all price-related variables (price, gain, loss, display, and feature). Indeed, research on deal proneness (Bawa and Shoemaker 1987; Blattberg et al. 1978) suggests that it is a consumer trait that exists across categories. Lichtenstein, Burton, and Netemeyer (1997) find a consumer segment that exhibits deal proneness across many types of sales promotion. H_5, however, does not rule out category-specific effects, which are significant at the market level (Narasimhan, Neslin, and Sen 1996). Ainslie and Rossi (1998) find some evidence that marketing-mix sensitivities exhibit both individual-specific characteristics (i.e., a consumer who is price-sensitive in one category tends to be so in others as well) and category-specific characteristics (i.e., average price sensitivity is higher in certain categories than in others). Murthi and Srinivasan (1999), while suggesting that product evaluation propensity is an intrinsic household trait, also find that category-specific factors are an influence.

H_6: Lower income is associated with higher (a) loss and (b) gain sensitivity.

H_7: Larger household size is associated with higher (a) loss and (b) gain sensitivity.

H_8: Less-than-full employment of the household head is associated with higher (a) loss and (b) gain sensitivity.

H_9: Households with better-educated heads tend to be more (a) loss- and (b) gain-sensitive.

Lower income, larger households, and household heads who are less than fully employed all imply tighter budget constraints, which should increase consumer involvement with shopping and motivation for price information storage and retrieval and lead to cognitive elaboration of price information. Their opportunity cost of time (required for cognitive elaboration) also is expected to be less. More education, however, may be associated with greater ability to process, store, and recall price information. Han, Gupta, and Lehmann's (1993) results provide some support, in that households with greater sensitivity to gains and losses were less likely to have fully employed household heads and had more education. However, education, employment status, and income are positively correlated, so we can expect the effects in H_6 and H_8 to offset those of H_9. Previous research using scanner-panel data has found little support for the impact of sociodemographics on marketing-mix sensitivities and choice. This may be partly due to the use of latent-class approaches, which are not effective in picking up relatively weaker drivers of choice. Using continuous approaches to model unobserved consumer heterogeneity, Keane (1997) finds that income and household size affect consumer price sensitivity.

THE MODEL

We estimate the relationship between consumer sensitivities to use experience, price, gain, loss, and so forth. As others have in the past (e.g., Erdem 1996; Keane 1997), we employ a brand-choice model with continuous, correlated multivariate distributions. We first discuss the utility specification and then describe the specifications of heterogeneity within and between product categories. Finally, we present formulae for choice probabilities and log-likelihood.

Utility Specification

Let I be the number of consumers (households) in the panel and T_i be the number of purchase occasions for consumer i. Consider a general model in which consumer i = 1, 2, ..., I on any purchase occasion t = 1, 2, ..., T_i chooses a single brand j from a set of j = 1, 2, ..., J distinct items in a product category.[3] Assume that the (indirect) utility this consumer derives from the purchase of this item is a linear function of preference, use experience, price, loss and gain relative to reference price, promotion, and demographic interaction variables.[4] This yields utilities U_{ijt}, j = 1, 2, ..., J, that consumer i would derive from purchasing brand–size combination (item) j on purchase occasion t:

$$
\begin{aligned}
(1)\quad U_{ijt} &= \alpha_{ij} + \beta_{1i}\,UE_{ijt} + \beta_{2i}\,PR_{ijt} + \beta_{3i}\,LOSS_{ijt} + \beta_{4i}\,GAIN_{ijt} \\
&+ \beta_{5i}DISPLAY_{ijt} + \beta_{6i}\,FEATURE_{ijt} \\
&+ \beta_{7i}D_{FSIZE_i}PR_{ijt} + \beta_{8i}D_{INCOME_i}PR_{ijt} + \beta_{9i}D_{EMP_i}PR_{ijt} \\
&+ \beta_{10i}D_{EDU_i}PR_{ijt} + \beta_{11i}D_{FSIZE_i}LOSS_{ijt} \\
&+ \beta_{12i}D_{INCOME_i}LOSS_{ijt} + \beta_{13i}D_{EMP_i}LOSS_{ijt} \\
&+ \beta_{14i}D_{EDU_i}LOSS_{ijt} + \beta_{15i}D_{FSIZE_i}GAIN_{ijt} \\
&+ \beta_{16i}D_{INCOME_i}GAIN_{ijt} + \beta_{17i}D_{EMP_i}GAIN_{ijt} \\
&+ \beta_{18i}D_{EDU_i}GAIN_{ijt} + \varepsilon_{ijt},
\end{aligned}
$$

where α_{ij} is a brand–size and consumer-specific constant; β_{ik}, k = 1, 2, ..., 18, are the response parameters; and ε_{ijt} is an error term whose properties will be specified subsequently.

UE_{ijt} is the use experience for consumer i of brand j on purchase occasion t. We operationalize UE_{ijt} as the weighted average of past purchases as do Guadagni and Little (1983):

$$(2)\quad UE_{ijt} = \kappa UE_{ijt-1} + (1-\kappa)D_{ijt-1}, \quad 0 \le \kappa \le 1.$$

Here, D_{ijt} is an indicator variable such that $D_{ijt} = 1$ if consumer i purchased brand–size combination j on purchase occasion t, whereas $D_{ijt} = 0$ otherwise.

We use two reference-price terms, LOSS and GAIN. GAIN is the difference, in cents per ounce, between the price (PR) and reference price (RP) for that item, given that RP is higher than PR. Similarly, LOSS is the difference given that RP is lower than PR. The current reference price, RP_{ijt}, is a weighted average of the reference price and price from the last purchase occasion:

$$(3)\quad LOSS_{ijt} = \max\{PR_{ijt} - RP_{ijt}, 0\};$$

$$(4)\quad GAIN_{ijt} = \max\{RP_{ijt} - PR_{ijt}, 0\};$$

and

$$(5)\quad RP_{ijt} = \eta RP_{ijt-1} + (1-\eta)PR_{ijt-1}, \quad 0 \le \eta \le 1.$$

We use item-specific IRPs rather than the category-level ERPs suggested by Hardie, Johnson, and Fader (1993). This is a common formulation (Kalyanaram and Little 1994; Krishnamurthi, Mazumdar, and Raj 1992; Lattin and Bucklin 1989; Mayhew and Winer 1992; Winer 1986). Consumers may use both IRPs and ERPs (e.g., Mayhew and Winer 1992; Rajendran and Tellis 1994), but we focus on IRPs because our interest lies in profiling consumers in regard to their sensitivity to their exposure to past prices. This has been the most common formulation in previous reference-price research. It is also in accord with the work of Briesch and colleagues (1997), who compare reference-price formulations and find that an internal, brand-specific formulation fits best. Furthermore, as shown in the next section, we estimate a large number of parameters to make statistical inference regarding correlations among various parameters within and across categories. Adding ERPs to the profiling analysis would render the estimation infeasible. Further research can attempt to profile ERP shoppers.

Including both price and reference-price terms has been common since Winer's (1986) seminal article. This is justified, because they play different roles and involve different

[3]Rather than assume a hierarchical decision, in which either brand or size is primary, we model each brand–size combination as a separate item. Therefore, J is the number of brand–size combinations.

[4]We avoid behavioral variables (e.g., purchase frequency), because they cause endogeneity problems.

behavioral mechanisms: comparing brands at a purchase occasion versus comparing brands' prices over time.

$DISPLAY_{ijt}$ and $FEATURE_{ijt}$ are dummy variables indicating the presence of a display or newspaper advertising feature. We also use dummies for sociodemographics: $D_{FSIZEij} = 1$ if the household at least four members, $D_{INCOME} = 1$ for annual household income of \$40,000 or higher, $D_{EMPi} = 1$ if a household head is fully employed, and $D_{EDUi} = 1$ if a household head has at least a college degree.[5]

Heterogeneity Specification

We assume a multinormal distribution for brand preferences $\alpha_i = (\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{iJ})^T$ and response parameters $\beta_i = (\beta_{1i}, \beta_{2i}, \ldots, \beta_{18i})^T$ (T denoting the transpose) with the following mean vector and covariance matrix[6]:

$$(6) \qquad \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \sim N\left\{ \begin{bmatrix} \alpha \\ \beta \end{bmatrix}, \begin{bmatrix} \Sigma_\alpha & 0 \\ 0 & \Sigma_\beta \end{bmatrix} \right\}.$$

As shown in Equation 6, α_i and β_i are assumed to be uncorrelated. The vectors α and β are the means, and the block diagonal matrices Σ_α and Σ_β are the covariance matrices of α_i and β_i, respectively. We denote the elements of Σ_α and Σ_β as $\sigma_{\alpha k}{}^2 = \Sigma_{\alpha kl}$, k, l = 1, 2, ..., J, and $\sigma_{\alpha k}{}^2 = \Sigma_{\beta mn}$, m, n = 1, 2, ..., 18, respectively (i.e., $\sigma_{\alpha k}$ and $\sigma_{\beta m}$ are the standard deviations of α_{ik} and β_{mi}, respectively), and the correlations are as follows:

$$(7) \qquad \rho_{akl} = \frac{\Sigma_{akl}}{\sigma_{ak}\sigma_{al}}, \quad k, l, = 1, 2, \ldots, J;$$

$$\rho_{\beta mn} = \frac{\Sigma_{\beta mn}}{\sigma_{\beta m}\sigma_{\beta n}}, \quad m, n, = 1, 2, \ldots, 18.$$

For example, $\rho_{\beta 54}$ is the correlation between gain sensitivity and display sensitivity. If this correlation is positive, it means that a consumer who is gain-sensitive is also likely to be display-sensitive. Similarly, $\rho_{\beta 53}$ is the correlation between loss and display sensitivities. In this case, a negative correlation coefficient would suggest that a loss-sensitive consumer is also more likely to be display-sensitive than the average consumer. Thus, the interpretation of a positive or negative correlation coefficient depends on the coefficient signs of the two variables in question.

Cross-Category Correlation

We estimate Equation 1 in three product categories, allowing cross-category correlations to examine whether consumers who are gain- or loss-sensitive in one category are so in another:

$$(8) \qquad \begin{bmatrix} \beta'_{1i} \\ \beta'_{2i} \\ \beta'_{3i} \end{bmatrix} \sim N\left\{ \begin{bmatrix} \beta'_1 \\ \beta'_2 \\ \beta'_3 \end{bmatrix}, \begin{bmatrix} \Sigma'_{\beta 1} & \Pi_{\beta 12} & \Pi_{\beta 13} \\ \Pi_{\beta 12} & \Sigma'_{\beta 2} & \Pi_{\beta 23} \\ \Pi_{\beta 31} & \Pi_{\beta 32} & \Sigma'_{\beta 3} \end{bmatrix} \right\}.$$

The subscripts 1, 2, and 3 in Equation 8 denote product categories, and the prime indicates the relevant vectors and matrices for the first six entries (use experience, price, loss, gain, display, and feature) of the parameter vectors β_{1i}, β_{2i}, and β_{3i}. Equation 8 introduces cross-category covariance matrices of the response coefficients, Π_β, whose nonzero entries are the cross-category covariances of use experience, price, loss, gain, display, and feature sensitivities. Three categories, therefore, yield 6 × 3 = 18 corresponding cross-category correlations to be estimated.

Choice Probabilities

Let us rewrite Equation 1 for each category d = 1, 2, 3 as

$$(9) \qquad U_{dijt} = V_{dijt} + \varepsilon_{dijt},$$

where

$$\begin{aligned}
(10) \quad V_{dijt} = {} & \alpha_{dij} + \beta_{d1i}\, UE_{dijt} + \beta_{d2i}\, PR_{dijt} + \beta_{d3i}\, LOSS_{dijt} \\
& + \beta_{d4i}\, GAIN_{dijt} + \beta_{d5i} DISPLAY_{dijt} \\
& + \beta_{d6i}\, FEATURE_{dijt} + \beta_{d7i} D_{FSIZE_i} PR_{dijt} \\
& + \beta_{d8i} D_{INCOME_i} PR_{dijt} + \beta_{d9i} D_{EMP_i} PR_{dijt} \\
& + \beta_{d10i} D_{EDU_i} PR_{dijt} + \beta_{d11i} D_{FSIZE_i} LOSS_{dijt} \\
& + \beta_{d12i} D_{INCOME_i} LOSS_{dijt} + \beta_{d13i} D_{EMP_i} LOSS_{dijt} \\
& + \beta_{d14i} D_{EDU_i} LOSS_{dijt} + \beta_{d15i} D_{FSIZE_i} GAIN_{dijt} \\
& + \beta_{d16i} D_{INCOME_i} GAIN_{dijt} + \beta_{d17i} D_{EMP_i} GAIN_{dijt} \\
& + \beta_{d18i} D_{EDU_i} GAIN_{dijt}.
\end{aligned}$$

Let θ denote the vector of parameters—α_1, α_2, α_3, β_1, β_2, β_3, $v(\Sigma_{\alpha 1})$, $v(\Sigma_{\alpha 2})$, $v(\Sigma_{\alpha 3})$, $v(\Sigma_{\beta 1})$, $v(\Sigma_{\beta 2})$, $v(\Sigma_{\beta 3})$, $w(\Pi_\beta)$, κ_1, η_1, κ_2, η_2, κ_3, η_3—where subscripts 1, 2, and 3 denote product categories. In this, v(.) is the transformation that stacks the upper diagonal entries of its square argument matrix into a vector. Likewise, w(.) is the transformation that stacks all the entries of its square argument matrix into a vector. Although we used the covariance matrices in defining the previous parameter vector for notational convenience, we estimate the corresponding standard deviations and correlations described previously instead of the covariances. We need a restriction on α_d, d = 1, 2, 3, because of the well-known invariance property of the logit probabilities shown in Equation 11. One such restriction is $\Sigma_{j=1}^{J} \alpha_{dj} = 0$, d = 1, 2, 3, which we now impose. Therefore, we estimate only J – 1 intercepts for each category.

All coefficients in Equation 10 are allowed to be heterogeneous across consumers, in keeping with their distributions as given in Equations 6 and 8. Let φ_i denote the multivariate standard normal vector that generates these coefficients. Assume now that ε_{dijt} is i.i.d. extreme value across categories, consumers, brand–size combinations, and purchase occasions. We then can write the choice probabilities conditional on θ and φ_i as (McFadden 1974)

$$(11) \qquad Prob_{dijt}(\boldsymbol{\theta}, \boldsymbol{\varphi}_i) = \frac{\exp\{V_{dijt}(\boldsymbol{\theta}, \boldsymbol{\varphi}_i)\}}{\sum_{k=1}^{J} \exp\{V_{dikt}(\boldsymbol{\theta}, \boldsymbol{\varphi}_i)\}}.$$

A household's probability of making the sequence of purchases D_{ijt}, conditional on θ and φ_i, is

[5]We checked whether the results are sensitive to other cutoff points and found that they are not.

[6]Research on heterogeneity in discrete choice models indicates that parameter estimates and model fit are not sensitive to distributional assumptions (i.e., normal versus some other distribution) (e.g., Keane, Moffitt, and Runkle 1988; Newey, Powell, and Walker 1990).

$$(12)\qquad \mathrm{Prob}_{di}(\boldsymbol{\theta}, \boldsymbol{\varphi}_i) = \prod_{t=1}^{T_i} \prod_{j=1}^{J} \mathrm{Prob}_{dijt}(\boldsymbol{\theta}, \boldsymbol{\varphi}_i)^{D_{dijt}}.$$

Integrating over φ_i (with Ω as the domain of the integration) and letting $f(\boldsymbol{\varphi}_i \,|\, \boldsymbol{\theta})$ represent the multinomial probability distribution function for φ_i, conditional on θ, yields

$$(13)\qquad \mathrm{Prob}_{di}(\boldsymbol{\theta}) = \int_{\Omega} \mathrm{Prob}_{di}(\boldsymbol{\theta}, \boldsymbol{\varphi}_i)\; f(\boldsymbol{\varphi}_i \,|\, \boldsymbol{\theta})\, d\boldsymbol{\varphi}_i.$$

Given Equation 10, the log-likelihood function to be maximized is

$$(14)\qquad \mathrm{Log}\, L_d(\boldsymbol{\theta}) = \sum_{i=1}^{I} \ln\,[\mathrm{Prob}_{di}(\boldsymbol{\theta})].$$

Calculating $\mathrm{Prob}_{di}(\boldsymbol{\theta})$ in Equation 13 requires evaluating high-dimension multiple integrals, which precludes traditional numerical integration methods. Instead, we use simulated maximum likelihood techniques employing Monte Carlo methods (Keane 1993; McFadden 1989; Pakes 1987).

DATA

Although many studies of reference price have used multiple data sets, none has allowed for reference-price sensitivity to be correlated across categories. We use ACNielsen Company scanner-panel data on ketchup, peanut butter, and tuna, which are categories with a limited number of major brands. We deleted minor items, which were operationalized in two ways: (1) any item with less than 2% share in the household-level data and (2) any item without at least a 3% share in the household-level data or a 3% share in at least one store in the store-level data. To delete items with "spotty" price data, we dropped any item without observations in at least 70% of the weeks in stores where it was available. In addition, households needed to pass three cutoffs in every product category to be included in the data set for any category. First, because we drop some brand–sizes as explained previously, the household needed to have at least 70% of its purchases included in the set of modeled brand–sizes. Second, it needed to have at least two purchases in the 52-week period used to initialize the reference-price and use-experience variables. Finally, it needed at least three purchases in the 73-week modeling period. The summary statistics are given in Table 1.

Table 1

SUMMARY STATISTICS

Brand Name	*Sample Frequency*	*Average Price*[a]
Ketchup		
Heinz 14 oz. (1)[b]	1.2%	5.77
Heinz 28 oz. (2)	9.5%	4.98
Heinz 32 oz. (3)	45.5%	3.70
Heinz 44 oz. (4)	3.9%	4.54
Heinz 64 oz. (5)	5.7%	4.55
Hunt's 32 oz. (6)	13.9%	3.43
Del Monte 32 oz. (7)	17.1%	3.42
Store brand 32 oz. (8)	3.3%	3.01
Peanut Butter		
Jif 12 oz. (1)	3.4%	11.04
Jif 18 oz. (2)	12.4%	10.07
Jif 28 oz. (3)	9.9%	10.15
Peter Pan 18 oz. (4)	24.1%	1.15
Skippy 18 oz. (5)	18.4%	10.01
Skippy 28 oz. (6)	10.2%	10.00
Skippy 40 oz. (7)	3.3%	9.85
Store brand 18 oz. (8)	15.2%	7.60
Store brand 28 oz. (9)	3.2%	8.38
Tuna (all 6.5 oz.)		
Star Kist (oil) (1)	15.67%	26.96
Star Kist (water) (2)	14.94%	24.36
Chicken of the Sea (oil) (3)	17.20%	19.65
Chicken of the Sea (water) (4)	17.16%	25.08
Private label (oil) (5)	20.06%	24.32
Private label (water) (6)	23.12%	19.44

[a]Average price in cents per ounce.

[b]We numbered each brand–size combination to assist the reader in identifying the different brand–size combinations in Table 3.

EMPIRICAL RESULTS

We estimated the full model (FM) given in Equations 1 through 8, as well as two models nested in FM. The first nested model (NM1) restricts the correlations among the consumer response heterogeneity distributions and cross-category correlations to be zero. The second nested model (NM2) restricts only the cross-category correlations to be zero. As shown in Table 2, the likelihood-ratio test suggests that NM2 fits the data better than NM1 and its improvement in in-sample fit and out-of-sample fit are statistically significant at the 1% confidence level in all categories. Because the FM has shared parameters across categories and the number of parameters cannot be assigned on a per-category basis, we computed an overall likelihood by summing up category-level likelihood statistics and conducted likelihood-ratio tests based on this overall likelihood. This likelihood-ratio test suggests that FM fits the data better than NM2, and its improvement in in-sample fit and out-of-sample fit are statistically significant at the 1% confidence level. Therefore, we report the parameter estimates for the FM only. Table 3 reports the within-category parameter estimates. Table 4 reports the cross-category parameter estimates.[7]

In all categories, main effects have the expected signs (i.e., positive signs for use experience, display, feature, and gain; negative signs for price and loss) and, with the exception of the gain coefficient for tuna, are statistically significant. We also find heterogeneity in the coefficients of all main effects (as shown by the statistically significant standard deviations), with the exception of gain in tuna.

Parameter intervals ranging two standard deviations from the mean for loss are wide compared with those for gain. For example, the loss interval for ketchup would be –.95 to .09,

[7]We do not report the variance–covariance matrix of brand constants because of the article's large number of tables and its focus on other issues. These estimates can be obtained from the authors. We estimate these variances and covariances with a single-factor method, which greatly reduces the number of parameters estimated. Estimating the full variance–covariance matrix requires 79 parameters (28, 36, and 15 parameters for the 8, 9, and 6 brands of ketchup, peanut butter, and tuna, respectively). Of these 79 elements, 20 are the standard deviations of constant term (preference) heterogeneity distributions, and 59 are the covariances. Instead, we impose a one-factor structure on the variance–covariance matrix of brand constants and estimate only 37 parameters (13, 15, and 9 parameters for ketchup, peanut butter, and tuna, respectively), from which we derive the full variance–covariance matrix with 79 elements. We report only 20 (7, 8, and 5 standard deviations of brand-specific constants for ketchup, peanut butter, and tuna, respectively) of these 79 elements in Table 3.

Table 2
MODEL SELECTION

Parameters		*NM1*[a]	*NM2*[b]	*FM*[c]
In-Sample (Chicago)[d]				
Ketchup	–LL	1983.8	1807.9	1773.3
	AIC	2025.8	1864.9	
	BIC	2140.3	2020.3	
Peanut butter	–LL	1762.8	1629.2	1574.6
	AIC	1807.8	1689.2	
	BIC	1924.5	1844.9	
Tuna	–LL	2082.6	2026.3	1867.8
	AIC	2118.6	2077.3	
	BIC	2217.9	2217.9	
Overall (summed across three categories)	–LL	5829.2	5463.4	5215.7
	AIC	5952.2	5631.4	5401.7
	BIC	6351.5	6176.8	6005.6
Out-of-Sample (Atlanta)[e]				
Ketchup	–LL	963.1	866.8	795.2
	AIC	1005.1	923.8	
	BIC	1104.8	1059.1	
Peanut butter	–LL	943.0	810.2	717.4
	AIC	988.0	870.2	
	BIC	1092.0	1008.8	
Tuna	–LL	922.3	826.4	775.6
	AIC	958.3	877.4	
	BIC	1043.1	997.5	
Overall (summed across three categories)	–LL	2828.4	2503.4	2288.2
	AIC	2951.4	2671.4	2474.2
	BIC	3307.7	3158.1	3013.0

[a]NM1 has 123 parameters across all three categories (42, 45, and 36 parameters estimated for ketchup, peanut butter, and tuna, respectively). Among these parameters, 37 are for estimating the variance–covariance matrix of the constant terms (13, 15, and 9 parameters for ketchup, peanut butter, and tuna, respectively), and 86 are for estimating the means of constant terms (brand-specific preferences) and means and standard deviations of coefficients for explanatory variables (29, 30, and 27 parameters for ketchup, peanut butter, and tuna, respectively).

[b]NM2 has 168 parameters across all three categories (57, 60, and 51 parameters estimated for ketchup, peanut butter, and tuna, respectively). Among these parameters, 37 are for estimating the variance–covariance matrix of constant terms, 86 are for estimating the means of constant terms and means and standard deviations of the coefficients for the explanatory variables, and 45 are for estimating within-category correlations (15 parameters in each of the three categories).

[c]The FM has 186 parameters. Among these parameters, 37 are for estimating the variance–covariance matrix of constant terms, 86 are for estimating the means of constant terms and means and standard deviations of the coefficients for the explanatory variables, 45 are for estimating within-category correlations, and 18 are for estimating the cross-category correlations. In Table 3, we report the 86 estimates for means of constant terms and means and standard deviations of the coefficients for the explanatory variables, 45 within-category correlations, and the 20 standard deviations of constant terms calculated from the 37 estimated parameters of the variance–covariance matrix of brand constants. The 18 cross-category correlations are reported in Table 4. The only estimates we do not report, to avoid additional tables, are the 59 additional elements of the variance–covariance matrix of brand constants, calculated from the 37 parameters of the variance–covariance matrix estimated.

[d]In total, 100 households made 1722 purchases of ketchup, 79 households made 1324 purchases of peanut butter, and 126 households made 1835 purchases of tuna.

[e]In total, 58 households made 853 purchases of ketchup, 41 households made 751 purchases of peanut butter, and 57 households made 822 purchases of tuna.

Notes: AIC = Akaike's information criterion, LL = log-likelihood.

whereas for gain the interval would be only –.01 to .15. Thus, gain effects are relatively small in magnitude and vary little over the population. Loss effects are much greater and exhibit much more heterogeneity. This is consistent with the implications of prospect theory and previous empirical findings that decision makers tend to be more loss averse than gain seeking. We find only weak evidence of an overall reference-price effect. Correlations between gain and loss sensitivities are negative for all categories, as would be expected (i.e., loss-sensitive consumers tend to be gain-sensitive), but are statistically significant only for ketchup.

In regard to our formal hypotheses, we fail to reject H_1 (i.e., our expectations are empirically validated). Correlations between price and loss sensitivities have the expected sign and are statistically significant (.45, .51, .and 40 for ketchup, peanut butter, and tuna, respectively). The same is true for correlations between price and gain sensitivities (–.23, –.24, and –.26 for ketchup, peanut butter, and tuna, respectively). These correlations are not extremely high in magnitude, which suggests that reference-price sensitivity is a separate phenomenon, rather than just another dimension of price sensitivity itself. Correlations are stronger for losses than for gains. Thus, although price-sensitive consumers are more loss- and gain-sensitive than the average consumer, they are even more likely to be loss-sensitive than gain-sensitive.

The results also support H_2 and H_3, in that both loss- and gain-sensitive consumers are more display- and feature-sensitive. Correlations between loss and display or feature are significantly negative, and the corresponding correlations for gains are significantly positive. Although they are significant, however, the greatest correlation is only –.27, again suggesting that reference-price sensitivity is distinct from other sensitivities.

H_{4a} is well supported. In all categories, consumers with higher use-experience sensitivities (less brand switching) are less sensitive to price increases (have lower loss sensitivities). However, support for H_{4b} is weak. Consumers with lower use sensitivity are more responsive to price cuts only for peanut butter. In the case of tuna, for which we did not find statistically significant gain sensitivity, this is not surprising.

H_5 is also supported, in that all loss and gain (as well as other) cross-category correlations are positive and significant (see Table 4). In addition, the similarities of correlations across categories are striking (see Table 3). We view this as evidence that reference-price sensitivity is not a purely category-specific phenomenon. This may be due in part to the categories we have modeled: All are shelf-stable foods (allowing for consumer stockpiling) dominated by strong national brands. However, there are interesting differences in pricing among the categories. Prices are different in absolute levels, price per ounce, and range (e.g., the mean price per ounce range is 3.0 to 6.0 for ketchup, 8.4 to 11.5 for peanut butter, and 15.7 to 20.4 for tuna). Mean category expenditure per purchase occasion also varies widely over the categories ($1.32, $2.14, and $4.38 for ketchup, peanut butter, and tuna, respectively), as does mean interpurchase time (50, 45, and 32 days for ketchup, peanut butter, and tuna, respectively). Thus, despite differences in price levels, purchase frequencies, and so forth, reference-price effects across categories are similar. This suggests that reference-price sensitivity is part of the consumer's general

Table 3
WITHIN-CATEGORY MODEL ESTIMATION

Parameters		*Ketchup*	*Peanut Butter*	*Tuna*
Brand–size-specific constants α	Brand 1	−.55 (.26)	.33 (.05)	4.33 (.17)
	Brand 2	1.48 (.38)	1.88 (.11)	3.77 (.12)
	Brand 3	2.93 (.22)	1.86 (.10)	.89 (.10)
	Brand 4	.87 (.25)	2.35 (.33)	.77 (.09)
	Brand 5	.78 (.17)	2.20 (.29)	.09 (.03)
	Brand 6	1.51 (.15)	1.00 (.21)	
	Brand 7	1.50 (.27)	−.17 (.04)	
	Brand 8		1.48 (.30)	
Standard deviation of brand–size-specific constant σ_α	Brand 1	2.15 (.33)	.83 (.32)	2.79 (.23)
	Brand 2	1.02 (.28)	.85 (.17)	2.80 (.16)
	Brand 3	.43 (.22)	1.02 (.25)	.89 (.16)
	Brand 4	2.84 (.22)	.76 (.21)	.51 (.12)
	Brand 5	.38 (.24)	.49 (.21)	.11 (.03)
	Brand 6	.58 (.18)	.11	(.05)
	Brand 7	.70 (.13)	.66	(.20)
	Brand 8		.59 (.22)	
Mean UE coefficient β_1		2.37 (.34)	1.73 (.31)	2.27 (.49)
Standard deviation of UE coefficient $\sigma_{\beta 1}$		1.23 (.36)	1.33 (.16)	1.59 (.64)
Mean price coefficient β_2		−1.48 (.11)	−.80 (.08)	−1.48 (.32)
Standard deviation of price coefficient $\sigma_{\beta 2}$		1.30 (.38)	.61 (.15)	1.07 (.47)
Mean price loss coefficient β_3		−.43 (.09)	−.35 (.11)	−.59 (.08)
Standard deviation of price loss coefficient $\sigma_{\beta 3}$		.26 (.09)	.22 (.11)	.49 (.20)
Mean price gain coefficient β_4		.07 (.01)	.08 (.01)	.03 (.018)
Standard deviation of price gain coefficient $\sigma_{\beta 4}$		.04 (.003)	.05 (.007)	.009 (.007)
Mean display coefficient β_5		1.77 (.48)	1.84 (.53)	2.49 (.62)
Standard deviation of display coefficient $\sigma_{\beta 5}$		.62 (.33)	.91 (.42)	1.30 (.22)
Mean feature coefficient β_6		2.42 (.12)	1.70 (.21)	1.79 (.40)
Standard deviation of feature coefficient $\sigma_{\beta 6}$		1.00 (.20)	1.07 (.42)	1.10 (.28)
Mean family size × price coefficient β_7		−.54 (.22)	−.42 (.20)	−.44 (.18)
Standard deviation of the family size × price coefficient $\sigma_{\beta 7}$		.43 (.32)	.23 (.19)	.28 (.11)
Mean family size × loss coefficient β_{11}		−.19 (.09)	−.28 (.10)	−.27 (.11)
Standard deviation of the family size × loss coefficient $\sigma_{\beta 11}$		.16 (.07)	.18 (.07)	.20 (.07)
Mean Income × price coefficient β_8		.27 (.19)	.39 (.18)	.44 (.18)
Standard deviation of the income × price coefficient $\sigma_{\beta 8}$		.28 (.22)	.30 (.19)	.19 (.11)
Mean employment × loss coefficient β_{13}		.08 (.04)	.32 (.10)	.18 (.08)
Standard deviation of the employment × loss coefficient $\sigma_{\beta 13}$		.08 (.03)	.18 (.08)	.11 (.07)
UE smoothing parameter k		.80 (.08)	.69 (.24)	.76 (.10)
Reference price smoothing parameter η		.71 (.11)	.39 (.12)	.51 (.21)
Correlation between UE and price coefficients $\rho_{\beta 21}$		.36 (.07)	.34 (.07)	.32 (.10)
Correlation between UE and loss coefficients $\rho_{\beta 31}$		.17 (.07)	.12 (.06)	.15 (.07)
Correlation between UE and gain coefficients $\rho_{\beta 41}$		−.05 (.07)	−.06 (.03)	−.06 (.04)
Correlation between UE and display coefficients $\rho_{\beta 51}$		−.13 (.04)	−.14 (.05)	−.12 (.05)
Correlation between UE and feature coefficients $\rho_{\beta 61}$		−.12 (.04)	−.19 (.05)	−.09 (.05)
Correlation between price and loss coefficients $\rho_{\beta 32}$		.45 (.18)	.51 (.20)	.40 (.15)
Correlation between price and gain coefficients $\rho_{\beta 42}$		−.23 (.12)	−.24 (.11)	−.26 (.11)
Correlation between price and display coefficients $\rho_{\beta 52}$		−.37 (.12)	−.37 (.17)	−.28 (.13)
Correlation between price and feature coefficients $\rho_{\beta 62}$		−.34 (.02)	−.31 (.22)	−.32 (.23)
Correlation between loss and gain coefficients $\rho_{\beta 43}$		−.36 (.14)	−.35 (.21)	−.32 (.23)
Correlation between loss and display coefficients $\rho_{\beta 53}$		−.25 (.07)	−.25 (.13)	−.24 (.10)
Correlation between loss and feature coefficients $\rho_{\beta 63}$		−.25 (.07)	−.27 (.12)	−.20 (.11)
Correlation between gain and display coefficients $\rho_{\beta 54}$		.17 (.10)	.16 (.06)	.13 (.06)
Correlation between gain and feature coefficients $\rho_{\beta 64}$		.20 (.11)	.15 (.07)	.16 (.06)
Correlation between display and feature coefficients $\rho_{\beta 65}$		.65 (.22)	.60 (.24)	.39 (.11)

Notes: UE = use experience.

shopping "personality" in frequently purchased packaged good categories.

Although reference price has a strong individual-specific component, the results bear evidence to suggest that there are category-specific effects. For example, although we find that use-experience, price, display, and feature sensitivities, similar to loss and gain sensitivity, are significantly correlated across categories, note that all of these cross-category correlations are greater in magnitude than those for losses or gains. Thus, reference-price effects are more category specific than other brand-choice effects. This should not be surprising, because price, display, and feature effects require no memory. Use of memory suggests some level of category involvement. Although use experience would also require memory, it may be a simpler task than that required for reference-price use.

Our results offer only partial support for our hypotheses pertaining to sociodemographics. Larger households and households without a fully employed head are more sensitive to price increases in all product categories. (Interactions between loss and household size and between loss and employment status are negative and significant.) Thus, H_{7a}

Table 4
CROSS-CATEGORY CORRELATIONS

Parameters (Cross-Category Correlations)	*Correlations*
Between Ketchup and Peanut Butter	
Correlations between UE coefficients $\lambda_{\beta 11}$	.56 (.20)
Correlations between price coefficients $\lambda_{\beta 22}$	.67 (.18)
Correlations between price loss coefficients $\lambda_{\beta 33}$	.35 (.14)
Correlations between price gain coefficients $\lambda_{\beta 44}$	.28 (.10)
Correlations between display coefficients $\lambda_{\beta 55}$	.67 (.28)
Correlations between feature coefficients $\lambda_{\beta 66}$	.73 (.28)
Between Ketchup and Tuna	
Correlations between UE coefficients $\lambda_{\beta 11}$	.46 (.18)
Correlations between price coefficients $\lambda_{\beta 22}$	.68 (.17)
Correlations between price loss coefficients $\lambda_{\beta 33}$	.41 (.12)
Correlations between price gain coefficients $\lambda_{\beta 44}$	.23 (.08)
Correlations between display coefficients $\lambda_{\beta 55}$	.66 (.35)
Correlations between feature coefficients $\lambda_{\beta 66}$	.75 (.24)
Between Peanut Butter and Tuna	
Correlations between UE coefficients $\lambda_{\beta 11}$	.58 (.25)
Correlations between price coefficients $\lambda_{\beta 22}$	56 (.28)
Correlations between price loss coefficients $\lambda_{\beta 33}$	.39 (.16)
Correlations between price gain coefficients $\lambda_{\beta 44}$	.21 (.10)
Correlations between display coefficients $\lambda_{\beta 55}$	.71 (.30)
Correlations between feature coefficients $\lambda_{\beta 66}$	.58 (.24)

Notes: UE = use experience.

and H_{8a} are supported. Loss's interactions with income and education, however, are insignificant, as are all interactions of gain and sociodemographic variables. Larger households and households with lower incomes are also more price-sensitive (price and family-size interactions are negative and significant; price and income interactions are positive and significant), consistent with Keane's (1997) findings. Also note that though income seems to affect price sensitivity, it does not affect loss or gain sensitivity. Also, whereas employment status affects loss sensitivity, it does not affect price sensitivity.

The rest of the correlation results can be summarized as follows: Households that are more sensitive to use experience tend to be less price-sensitive (significant, positive correlations) and less display- and feature-sensitive (significant, negative correlations). Consumers who are more price-sensitive also tend to be more display-sensitive (significant, negative correlations). Finally, display-sensitive consumers tend to be feature-sensitive as well. All these results hold for all categories. The only other result that does not hold for all categories is the correlation between price and feature sensitivity. It is significant and positive for ketchup but insignificant for peanut butter and tuna.

LATENT-CLASS MODELS

Most reference-price researchers have used latent-class models (Kamakura and Russell 1989) to segment the population. These models are easily estimated and generally yield a small number of consumer classes. However, latent-class models are not appropriate in certain contexts. For example, DeSarbo and colleagues (1997, p. 345) point out that "One of the profound difficulties encountered with finite mixture models is the fact that membership in the derived groups or segments typically relate weakly to any individual demographic or psychographic data."

The problem is that these variables, similar to reference prices, are generally secondary drivers of choice. More specifically, the variables that explain the greatest variance in brand choices (brand preferences, use experience, and price) have the greatest impact on segmentation in latent-class models (Keane 1997). Reference-price variables, though statistically significant, generally have smaller effects on brand choice. Indeed, the effects of reference-price variables in Bell and Bucklin's (1995), Mazumdar and Papatla's (1995), and Bell and Lattin's (2000) multisegment models are consistently smaller than those for brand preferences, loyalty, and price. The reference-price term in Bell and Bucklin's model is not statistically significant for any segment in either product category. Bell and Lattin find some statistically significant reference-price terms and suggest that loss aversion may not be a universal phenomenon, but they find only 2 product categories of 11 in which the gain in model fit from accounting for heterogeneity in loss aversion outweighs the loss of parsimony. It must be questioned how much such results are driven by the use of latent-class techniques.

We also estimated a latent-class version of our model to demonstrate the problems of using such techniques to profile consumers. In Table 5, we report the parameter estimates for the latent-class models for the three categories. In Table 6, we report in-sample goodness-of-fit statistics and out-of-sample (predictive) fit statistics for models with varying numbers of support or mass points (segments). Following the usual procedure in latent-class modeling, we chose the appropriate number of support points on the basis of the Bayesian information criterion (BIC). Table 6 reveals that the best-fitting model has three support points in ketchup, four in peanut butter, and two in tuna. A comparison of BICs of the best-fitting latent-class models in each category (Table 6) with those of our corresponding model shows that our model, with continuous heterogeneity distributions that allow correlation within a given category (NM2), outperforms latent-class models both in sample and out of sample for all categories. However, we should note that the in-sample BICs obtained from NM2 and the latent-class model are very similar in the case of tuna. This may be because there seems to be less heterogeneity in consumer preferences and responses in tuna compared with ketchup or peanut butter. Finally, as indicated previously, our FM outperforms NM2. Therefore, the FM outperforms the latent-class models we estimated.

Given that previous research has also shown that continuous approaches usually fit better then latent-class models (e.g., Elrod and Keane 1995), our results are not surprising. First, latent-class models assume within-segment homogeneity, though within-segment heterogeneity persists in such models (Heckman and Singer 1984), unmeasured in any way. Second, the extent of heterogeneity might be underestimated, because every new mass point (segment) adds a large number of parameters to the model. (For example, in the latent-class models presented in Table 5 and discussed subsequently, adding another mass point would add 18, 18, and 16 parameters, respectively, for ketchup, peanut butter, and tuna.) Because additional parameters are penalized in model comparisons based on likelihood-ratio tests or BICs, a relatively large increase in likelihood is needed to add further segments. Secondary drivers of choice are unable to generate such large likelihood gains. Consequently, the membership probabilities for these "superseg-

Table 5

ESTIMATION RESULTS OF MIXTURE MODEL

A: Ketchup							
Segment		*1*		*2*		*3*	
Membership probability π		.41	(.04)	.29	(.13)	.30	
Brand–size-specific constants α	Brand 1	–.38	(.10)	–1.11	(.42)	–.55	(.21)
	Brand 2	1.27	(.25)	.73	(.24)	1.29	(.28)
	Brand 3	2.93	(.35)	2.59	(.31)	3.08	(.38)
	Brand 4	1.30	(.51)	1.98	(.28)	1.29	(.37)
	Brand 5	.39	(.16)	1.32	(.19)	1.07	(.17)
	Brand 6	1.28	(.21)	1.82	(.18)	2.00	(.21)
	Brand 7	1.64	(.43)	2.33	(.72)	1.76	(.66)
Mean UE coefficient β_1		1.74	(.08)	1.35	(.07)	1.88	(.08)
Mean price coefficient β_2		–1.93	(.16)	–1.95	(.16)	–1.77	(.15)
Mean price loss coefficient β_3		–1.21	(.22)	–.96	(.16)	–.69	(.24)
Mean price gain coefficient β_4		.09	(.02)	.09	(.02)	.07	(.03)
Mean display coefficient β_5		1.54	(.58)	1.52	(.57)	1.61	(.59)
Mean feature coefficient β_6		1.85	(.37)	1.68	(1.59)	1.54	(.46)
Mean family size × price coefficient β_7		–.14	(.46)	–.37	(1.19)	–.63	(.66)
Mean family size × loss coefficient β_8		–.07	(.07)	–.20	(1.17)	–.21	(1.07)
Mean Income × price coefficient β_9		.23	(.31)	.27	(.20)	.29	(1.15)
Mean employment × loss coefficient β_{10}		.10	(.26)	.07	(.32)	.09	(1.06)
UE smoothing parameter k				.82	(.15)		
Reference price smoothing parameter η				.70	(.06)		

B: Peanut Butter									
Segment		*1*		*2*		*3*		*4*	
Membership Probability π		.16	(.04)	.36	(.13)	.19	(.07)	.29	
Brand–size-specific constants α	Brand 1	.41	(.12)	.28	(.09)	.57	(.11)	.52	(.20)
	Brand 2	1.69	(.30)	1.05	(.36)	1.38	(.41)	1.47	(.28)
	Brand 3	1.79	(.25)	1.29	(.28)	1.52	(.23)	1.38	(.25)
	Brand 4	2.36	(.38)	2.73	(.40)	3.08	(.45)	2.40	(.40)
	Brand 5	2.52	(.28)	2.81	(.24)	2.25	(.34)	2.78	(.17)
	Brand 6	1.69	(.37)	1.07	(.39)	1.94	(.23)	1.37	(.40)
	Brand 7	–.03	(.01)	–.31	(.12)	–.24	(.06)	–.19	(.05)
	Brand 8	1.33	(.35)	1.21	(.32)	1.56	(.23)	1.48	(.35)
Mean UE coefficient β_1		1.80	(.09)	1.81	(.10)	1.83	(.08)	1.81	(.17)
Mean price coefficient β_2		–1.00	(.13)	–1.06	(.09)	–1.85	(.11)	–1.67	(.11)
Mean price loss coefficient β_3		–.43	(.19)	–.38	(.17)	–.35	(.14)	–.30	(.16)
Mean price gain coefficient β_4		.08	(.02)	.09	(.02)	.07	(.03)	.06	(.03)
Mean display coefficient β_5		2.53	(.58)	2.02	(.48)	2.39	(.43)	2.15	(.43)
Mean feature coefficient β_6		2.05	(.25)	1.98	(.41)	1.93	(.35)	1.91	(.39)
Mean family size × price coefficient β_7		–.39	(.25)	–.35	(.30)	–.43	(.45)	–.41	(.40)
Mean family size × loss coefficient β_8		–.16	(1.08)	–.16	(.47)	–.18	(.10)	–.17	(.09)
Mean Income × price coefficient β_9		.42	(.43)	.36	(.40)	.38	(.23)	.24	(1.21)
Mean employment × loss coefficient β_{10}		.17	(.39)	.17	(.63)	.12	(.06)	.14	(.54)
UE smoothing parameter k				.74	(.18)				
Reference price smoothing parameter η				.49	(.08)				

C: Tuna					
Segment		*1*		*2*	
Membership probability π		.32	(.17)	.68	
Brand–size-specific constants α	Brand 1	5.34	(.75)	4.97	(.51)
	Brand 2	3.95	(.31)	2.77	(.36)
	Brand 3	.84	(.18)	1.01	(.22)
	Brand 4	1.25	(.24)	1.50	(.23)
	Brand 5	–.18	(.04)	.08	(.03)
Mean UE coefficient β_1		2.52	(.14)	2.09	(.12)
Mean price coefficient β_2		–1.68	(.19)	–1.95	(.12)
Mean price loss coefficient β_3		–.83	(.17)	–.91	(.19)
Mean price gain coefficient β_4		.07	(.03)	.08	(.04)
Mean display coefficient β_5		2.37	(.48)	2.29	(.34)
Mean feature coefficient β_6		1.63	(.30)	1.82	(.47)
Mean family size × price coefficient β_7		–.51	(.32)	–.29	(.15)
Mean family size × loss coefficient β_8		–.26	(.19)	–.20	(.18)
Mean Income × price coefficient β_9		.36	(.24)	.19	(.15)
Mean employment × loss coefficient β_{10}		.24	(.16)	.17	(.28)
UE smoothing parameter k			.79	(.17)	
Reference price smoothing parameter η			.54	(.08)	

Notes: UE = use experience.

Table 6
SAMPLE SELECTION FOR LATENT-CLASS MODEL

Product Categories		Number of Segments 1	2	3	4	5
In-Sample						
Ketchup	-LL	2073.8	1981.5	1898.4	1882.1	
	BIC	2144.6	2119.3	2103.3	2116.8	
Peanut butter	-LL	1891.2	1784.7	1709.0	1637.1	1581.4
	BIC	1963.1	1924.9	1917.5	1913.9	1926.4
Tuna	-LL	2232.0	2098.9	2103.3		
	BIC	2295.9	2222.9	2287.4		
Out-of-Sample						
Ketchup	-LL			1150.4		
	BIC			1355.3		
Peanut butter	-LL				1069.8	
	BIC				1346.6	
Tuna	-LL		935.6			
	BIC		1059.6			

Notes: LL = log-likelihood.

ments" are driven by the variables that explain most of the variance in brand-choice data, which is the important point given the purposes of this study.

The results in Table 5 show that differences in loss and gain sensitivities across segments are small (e.g., peanut butter loss sensitivity range of –.30 to –.43 and gain sensitivity range of .06 to .09), except for loss sensitivities in ketchup. Our FM with continuous and correlated sensitivities suggests much greater heterogeneity.[8] This may be due in part to misclassification in segment membership relative to reference-price sensitivities. Consider the latent-class model we estimated on ketchup data, which has 17 parameters (excluding segment membership probability) and therefore 2^{17} different groups if we make the extreme assumption that each variable has only two general sensitivity levels. The best-fitting latent-class model approximates all of these differences using only three segments. Such a restriction leads to segment membership probability being driven by variables that have strong effects on choice. The reason is quite simple. Every new mass point (segment) adds a large number of parameters to the model. Because additional parameters are penalized in model comparisons based on likelihood ratio tests or BICs, a relatively large increase in likelihood is needed to add further segments. Secondary drivers of choice are unable to generate such large likelihood gains, so consumers with identical responses to secondary drivers can wind up in different segments on the basis of their difference with respect to primary drivers, even if those differences are not extreme. Note that such misclassifications are likely as long as sensitivities to primary and secondary drivers are not highly correlated. Our empirical analysis shows that the correlation between reference-price sensitivities and other sensitivities, though statistically significant and large enough to draw policy implications, are generally less than .5, a level that would not make misclassifications unlikely.

However, an even more basic problem of latent-class approaches in profiling consumers on the basis of any variables, primary or secondary, is that statistical inference is not possible with respect to correlations among consumer sensitivities. Thus, researchers cannot test for a statistically significant correlation between, for example, reference-price sensitivity and display sensitivity. That is why Mazumdar and Papatla (2000) calculate display activity statistics from the data and attempt to link them to the IRP–ERP parameter estimate ex post. Although this type of analysis is useful as an exploratory study, any conclusions lack the weight of statistical significance.

The problem associated with latent-class models' inability to provide correlation coefficients is readily understood in an attempt to judge, on the basis of the latent-class model results in Table 5, whether loss and display sensitivity are related. All we can do is "eyeball" the results, which show no apparent pattern (though our continuous model found significant correlations). Indeed, the more variables the model has, the more difficult it becomes to detect any pattern. Although no statistical inference can be made, we can calculate correlation coefficients using the latent-class model's weighted segment parameters. As an example, we calculated the correlation between loss and price sensitivities and between loss and use-experience sensitivities for both ketchup and peanut butter. (Because tuna has only two segments, any correlation calculated would be 1 or –1.) Comparing these calculated correlations with those that we estimated in our continuous model and found to be statistically significant yields insightful results. For ketchup, the latent-class model yields a calculated correlation between loss and price sensitivities of .82 and between loss and use-experience sensitivities of .28. The corresponding correlations in our continuous model are .45 and .17. For peanut butter, the latent-class model yields correlations of –.79 and .46, whereas the estimated correlations in the continuous distribution model are .51 and .12. Therefore, not only are all of the correlations from the latent-class model inflated,

[8]Parameter estimates from our FM and latent-class models cannot be directly compared, but we can calculate the mean and standard deviation of parameters across latent classes (weighted by membership probabilities) and compare intervals with those of the FM. For example, for peanut butter, the weighted mean loss sensitivity is –.37 (S.D. = .2). A parameter interval ranging two standard deviations from the mean is (–.57, –.17), whereas the interval from the FM is (–.80, .11). Latent-class models tend to underestimate consumer heterogeneity. This tendency is greater for secondary drivers of choice, as the likelihood associated with misclassifying a secondary driver is higher. Therefore, if we were to compare interval estimates of brand preferences, we would find smaller differences than those shown for loss sensitivity.

but also the loss and price sensitivity correlation in peanut butter has the wrong sign.

Finally, prior researchers have had difficulty showing any effects of sociodemographics using latent-class models. We find this as well. Whereas the continuous distribution model found some significant interactions of sociodemographics with price and loss, the latent-class models show none, though they incorporate sociodemographics in various ways (e.g., constraining sociodemographic and reference-price interaction parameters to be the same across segments). If reference-price effects are secondary to preference, use experience, and price, sociodemographics might reasonably be termed "tertiary" effects. It is no surprise that latent-class models, which are unable to discriminate on the basis of secondary effects, would fail to find sociodemographics to be statistically significant.

CONCLUSION: MANAGERIAL IMPLICATIONS AND FURTHER RESEARCH

In this article, we attempted to profile reference-price shoppers. Our results suggest caution in viewing reference-price shoppers as both loss- and gain-sensitive. We find that the loss-sensitive shoppers are less influenced by past brand use and show stronger reactions to price, display, and feature than the average consumer. In addition, loss-sensitive households tend to be larger, and their heads are less likely to be fully employed. Gain-sensitive consumers are also more price-, display-, and feature-sensitive than the average consumer, but not to the degree that loss-sensitive consumers are. Gain-sensitive households do not tend to be much more use-sensitive than the average consumer, and they have no clear demographic profile. Loss sensitivity is much greater, on average, than gain sensitivity and shows wider heterogeneity. Although the weak heterogeneity of gain sensitivity may be interpreted as a sign that it is more ubiquitous than loss sensitivity, it is more likely a simple result of gain being a less important driver of choice. Loss and gain sensitivity also appear to be general shopping traits, and sensitivities are correlated across categories.

The most common managerial implication of reference prices discussed in the literature is the danger of price promotions hurting a brand's loyal franchise by lowering reference prices and thereby lowering choice probabilities in postpromotional periods. The support for prospect theory in prior research should heighten fears regarding promotions, because the gain from a temporary promotion is more than offset by the sting of prices rising when the promotion ends. The finding that use-experience–sensitive consumers are less sensitive to price increases suggests that the sting of the postpromotion price increase is less severe for brand-loyal customers. Indeed, it is ironic that brands with more loyal followings may suffer less loss-aversion damage from promotions, while being less dependent on promotions to gain sales from "brand switchers."

Our results suggest that displays and features are more likely to affect price-sensitive and price-conscious shoppers, because consumers who are more responsive to displays and features tend to be more sensitive to price, losses, and gains. Our results also suggest that brands that attract larger households or those whose heads are less than fully employed should be more concerned about the long-term impact of promotions. These households tend to be more price- and loss-sensitive. Thus, if Hunt's is more dependent on such households than Heinz is (Quelch 1985), Hunt's should be cognizant that its customers will be more sensitive to postpromotion price increases than will Heinz's customers.

Perhaps the most important managerial implication arises from the increasing amount of information that retailers are gathering as retail frequent-shopper programs proliferate. A retailer could easily use such data to segment customers on the basis of sociodemographics that correlate with loss and gain sensitivity. For example, managers could identify larger families and adjust promotion strategies at the household level through direct mail or other targetable media. In addition, a chain could adjust features, advertising strategies, coupons, and so forth depending on the customer base of the individual stores.

Finally, our results suggest that price-, promotion-, and reference-price–sensitive customers tend to be so across categories. Therefore, if increasing promotions to such households can increase their overall reference-price sensitivity in the long run, it can have a harmful effect even on categories that are not promoted. Regarding reference prices of individual items, however, the store manager has the luxury not available to the brand manager of rotating promotions among brands in the category, as well as across categories. In this way, individual brand reference prices are less affected.

Further research is necessary to identify the psychological characteristics of reference-price shoppers to understand individual-level effects more clearly. Further cross-category research could identify the characteristics of categories with high reference-price sensitivities or high heterogeneity. Finally, the analysis could be extended from brand choice to joint brand, quantity, and purchase-timing decisions. This would help achieve a more complete picture of reference-price shoppers by providing insights into the interrelationships between reference prices and behavioral variables such as usage rates, frequency of purchases, and purpose of the shopping trip.

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