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Profiling the reference price consumer

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Abstract

Researchers in marketing have devoted considerable attention to understanding how price impacts the purchase decision. Some individuals, termed memory-based reference price (MBR) consumers, take into account price expectations developed from past purchase behavior when making a current choice. Other individuals, termed stimulus-based reference price (SBR) consumers, make choices by constructing a reference point from the currently observed distribution of prices. Using a latent class model of structural heterogeneity applied to purchase histories from the toilet tissue category, we classify households in terms of the pricing mechanism used in buying decisions. We find strong evidence that memory-based (internal) reference price consumers are more price sensitive than other consumers. Moreover, we find that variables associated with the accessibility of price information are predictive of consumer use of memory-based reference prices. Managerial implications of these results are discussed.

Keywords: Reference price; Pricing strategy; Choice model; Structural heterogeneity model

Introduction

Consumers have distinctive price responses that reflect the manner in which they process price information. In most brand choice models, it is assumed that all consumers respond to observed prices without going through any subjective encoding of prices (Guadagni and Little 1983). That is, consumers are assumed to treat the observed price as the relevant decision variable in making a choice. In contrast, the reference price literature argues that consumers use psychologically encoded prices when making a choice (Winer 1986; Lichtenstein et al. 1991; Hardie et al. 1993; Briesch et al. 1997). Because the market-level reaction to price depends on the way consumers encode prices, it is important for both researchers and managers to understand the extent to which consumers use reference prices.

Reference price mechanisms

Broadly construed, the term reference price refers to the manner in which consumers use price information from the store environment. If consumers use price information that is based upon past shopping experiences, consumers are said to utilize a memory-based reference price (MBR) mechanism (Briesch et al. 1997). Typically, these consumers make utility assessments using the differential between current prices and some function of observed past prices. Although a number of memory-based pricing rules have been proposed, researchers commonly assume that consumers compare each brand price to a corresponding brand-specific reference price (Winer 1986; Lattin and Bucklin 1989; Erdem et al. 2001). Because this type of pricing mechanism leads to choice behavior that is strongly dependent on past purchase experience, the patterning of prices over time is an important issue for retailers.

In contrast, consumers may compare a brand's price to a reference price level based upon the current distribution of prices in the store. In such situations, consumers are said to have a stimulus-based reference price (SBR) mechanism because no memory of past prices is needed to encode brand price (Briesch et al. 1997). Although some researchers argue that a stimulus-based reference price is obtained from information due to marketing efforts (Mayhew and Winer 1992; Kopalle and Lindsey-Mullikin 2003), many researchers assume that consumers use a reference point constructed during the purchase occasion by observing shelf prices (Hardie et al. 1993; Bell and Lattin 2000; Mazumdar

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and Papatla 2000). If the consumer follows a stimulus-based model, reaction to price is strongly influenced by the extent to which a price is considered fair or reasonable. This mechanism can lead to surprising results for retailers. For example, under a stimulus-based reference price mechanism, a consumer may not react to a price decline if the new price remains above the consumer's reference price level.

Although early work assumes that consumers all follow one mechanism (MBR or SBR), more recent studies allow for heterogeneity in the pattern of responses. Mazumdar and Papatla (2000) develop hybrid models in which both MBR and SBR mechanisms are assumed to operate simultaneously. Erdem et al. (2001) assume that all consumers follow an MBR process, but that the parameters governing consumer reactions to reference price (perceived gains or losses) are heterogeneous across the population. These studies underscore the idea that individual differences play an important role in how consumers process price information.

Goals of research

In this research, we extend this literature on individual differences by positing that the market consists of three segments of consumers: an MBR segment that uses past prices recalled from memory, an SBR segment that uses the current distribution of brand prices, and a no reference price (NRP) segment that does not recode observed price information in any way. Consistent with work by Lynch et al. (1988), we argue that consumers must expend cognitive effort in recoding prices and therefore must possess sufficient motivation to do so. Accordingly, in studying reference price behavior, it is desirable to allow for an NRP segment that takes price information as given. From the standpoint of marketing theory, this three-segment approach also provides insight into the empirical validity of commonly used NRP choice models (Guadagni and Little 1983).

Using a model of structural heterogeneity (Kamakura et al. 1996), we classify consumers into reference price segments using choice histories from the toilet tissue category. Our empirical results for this category clearly show that all three segments exist, but that reference price consumers (MBR and SBR) constitute the majority of the market. Our results also provide strong evidence that MBR consumers differ from other consumers in the extent of their price knowledge. MBR consumers are more price sensitive than other consumers. Moreover, the likelihood of MBR membership correlates well with variables suggesting that MBR consumers monitor prices and plan ahead when making purchases. To summarize, our work both classifies consumers into price response segments and investigates differences in price sensitivity across these segments.

This paper is organized as follows. First, we formulate three different random utility models of price response (NRP, MBR, and SBR) and propose a methodology for determining which model best represents the choice behavior of a particular household. Second, using consumer choice histories from the toilet tissue product category, we empirically classify consumers into the three price response segments and use the model results to study correlates of these segments. We conclude with a discussion of theoretical and managerial implications of this research.

Typology of price responses

We assume that consumers can be classified as using one of three price response segments: memory-based reference price, stimulus-based reference price, or no reference price. In this section, we describe the choice model that characterizes each segment, and show how a latent class logit methodology may be used to sort consumers into the three segments.

No reference price (NRP) model

Most brand choice models do not consider any reference price effect beyond currently observed prices. Following standard practice (e.g., Guadagni and Little 1983), we write the utility of consumer h for brand j at time t as

$$U_{hjt} = \beta_0 + \beta_Y \mathrm{LOY}_{hjt} + \beta_P P_{hjt} + \beta_F F_{hjt} + \beta_D D_{hjt} + \varepsilon_{hjt} \quad (1)$$

where LOY is a loyalty variable measuring brand preference (defined subsequently), P is current brand price, F is the brand feature index, D is the brand display index, and ε is a random error with mean zero. Assuming that ε follows an extreme value distribution, the probability that consumer h purchases brand j at time t is given by the logit model

$$Pr(\text{buy } j|\text{NRP}) = \frac{\exp(Z_{hjt})}{\exp(Z_{h1t}) + \cdots + \exp(Z_{hBt})} \quad (2)$$

where $Z_{hjt} = \beta_0 + \beta_Y \mathrm{LOY}_{hjt} + \beta_P P_{hjt} + \beta_F F_{hjt} + \beta_D D_{hjt}$, and the denominator runs over all brands in the consumer's choice set.

From the perspective of this study, the key element of the NRP model is that price enters the model without further modification. Although it is clear from Eq. (2) that prices of different brands are compared in making a choice, the consumer does not recode price in any way prior to the choice decision. As detailed below, encoding brand price using additional information is the key feature of the MBR and SBR models.

Memory-based reference price (MBR) model

Reference price research in marketing literature is based upon adaptation level theory (Helson 1964) and prospect theory (Kahneman and Tversky 1979). Adaptation level theory suggests that a consumer's response to prices is affected by how the consumer adapts to past prices. This adaptation level is called the reference price. Prospect theory enriches this reference price model by bringing in a loss–gain concept.

Specifically, when the currently available price of the brand of interest is higher than the brand's reference price, the consumer perceives a loss buying the brand at the given price. Similarly, if the current brand price is lower than the brand's reference price, the consumer sees the price as a gain.

The two perspectives can be brought together by rewriting the NRP utility model of Eq. (1) as

$$U_{hjt} = \beta_0 + \beta_Y \mathrm{LOY}_{hjt} + \beta_P P_{hjt} + \beta_L (P_{hjt} - \mathrm{IRP}_{hjt})_+ + \beta_G (\mathrm{IRP}_{hjt} - P_{hjt})_+ + \beta_F F_{hjt} + \beta_D D_{hjt} + \varepsilon_{hjt} \tag{3}$$

where the notation $(x)_+$ denotes a variable which equals zero if x is negative and equals x if x is positive. Here, IRP denotes the internal reference price. By assuming that the random error ε has an extreme value distribution, we write the choice probability of the MBR model as

$$Pr(\text{buy } j|\text{MBR}) = \frac{\exp(Z_{hjt})}{\exp(Z_{h1t}) + \cdots + \exp(Z_{hBt})} \tag{4}$$

where $Z_{hjt} = \beta_0 + \beta_Y \mathrm{LOY}_{hjt} + \beta_P P_{hjt} + \beta_L (P_{hjt} - \mathrm{IRP}_{hjt})_+ + \beta_G (\mathrm{IRP}_{hjt} - P_{hjt})_+ + \beta_F F_{hjt} + \beta_D D_{hjt}$.

The MBR model predicts that consumers have a differential reaction to prices above and below the reference price level. When current price P is greater than IRP, the consumer experiences a loss: the β_L (loss) term impacts utility, while the β_G (gain) term is zero. When current price P is less than IRP, the consumer experiences a gain: the β_G (gain) term impacts utility, while the β_L (loss) term is zero. Because a loss decreases utility and a gain increases utility, we expect that $\beta_L < 0$ and $\beta_G > 0$. In addition, prospect theory predicts that the absolute value of β_L will exceed the absolute value of β_G because losses are perceived to be more important than gains (the loss aversion phenomenon).

The precise definition of the memory-based (or internal) reference price has been the subject of considerable research (Kalyanaraman and Winer 1995; Krishnamurthi et al. 1992; Mayhew and Winer 1992; Putler 1992; Briesch et al. 1997; Bell and Bucklin 1999). Following earlier work, we define IRP as the exponentially weighted average

$$\mathrm{IRP}_{hjt} = \lambda\, \mathrm{IRP}_{hj(t-1)} + (1-\lambda) P_{hj(t-1)} \tag{5}$$

where λ $(0 \le \lambda \le 1)$ is a smoothing parameter that determines the number of past prices that influence the current reference price value. Small values of λ imply that reference price approaches the price of the brand on the previous purchase occasion.

There exists some controversy about whether current price should be included in the MBR model along with loss and gain variables. Our research follows a general MBR model specification developed by Putler (1992). Using economic theory as a guide, Putler argues that current price reflects substitution across products, while the gain and loss variables represent the impact of reference price on utility. Accordingly, all three terms are needed.

Stimulus-based reference price (SBR) model

In contrast to the MBR model, we expect to see a different encoding process for a stimulus-based reference price consumer. These consumers do not base judgments upon prices observed during past purchase experiences. Instead of recalling prices from memory, SBR consumers are assumed to use information in the current choice environment to develop a suitable reference price value. However, once this reference price value is constructed, SBR consumers also evaluate price according to a loss and gain mechanism.

Drawing upon the MBR model specification, we define the utility of a SBR consumer as

$$U_{hjt} = \beta_0 + \beta_Y \mathrm{LOY}_{hjt} + \beta_L (P_{hjt} - \mathrm{SRP}_{hjt})_+ + \beta_G (\mathrm{SRP}_{ht} - P_{hjt})_+ + \beta_F F_{hjt} + \beta_D D_{hjt} + \varepsilon_{hjt} \tag{6}$$

where $(x)_+$ denotes a variable which equals zero if x is negative and equals x if x is positive. In this equation, SRP denotes the stimulus-based reference price value. Note that SRP depends upon both consumer h and time t, but is independent of brand. In addition, current shelf price P *does not* enter the model as a separate term. Again, by taking the random error to have an extreme value distribution, we can write the choice probability of an SBR consumer in the logit form as

$$Pr(\text{buy } j|\text{SBR}) = \frac{\exp(Z_{hjt})}{\exp(Z_{h1t}) + \cdots + \exp(Z_{hBt})}, \tag{7}$$

where $Z_{hjt} = \beta_0 + \beta_Y \mathrm{LOY}_{hjt} + \beta_L (P_{hjt} - \mathrm{SRP}_{ht})_+ + \beta_G (\mathrm{SRP}_{ht} - P_{hjt})_+ + \beta_F F_{hjt} + \beta_D D_{hjt}$.

The key feature of the SBR model is a global reference price value which is compared to all brands. Some researchers assume that the reference point arises from a salient cue provided by the retailer, such as a price point on an in-store display (Mayhew and Winer 1992; Kopalle and Lindsey-Mullikin 2003). In this research, we follow previous studies which assume that consumers use a reference point constructed at the point of purchase by examining the current shelf prices (Hardie et al. 1993; Mazumdar and Papatla 2000; Bell and Lattin 2000). Accordingly, the reference price in our SBR model has two key properties: it does not require the consumer to remember past prices, and it is not directly induced by retailer marketing actions.

Consistent with earlier work by Hardie et al. (1993), we define the reference price point of the SBR model to be the *current* price of the brand purchased on the *previous* purchase occasion (Kopalle et al. 1996; Briesch et al. 1997; Bell and Lattin 2000). Hardie et al. (1993) argue that memory of past choices is distinct from memory of past prices. Because grocery store buying behavior is a frequent activity, consumers often enter the store with some knowledge of the most recently purchased product in the category. For this reason, the SBR consumer can use the identity of the previous brand as a focal point for encoding the set of current shelf prices. As noted by Hardie et al. (1993), the previous brand purchased is a natural anchor for the consumer: it is much easier to remember than the price history, and simplifies the choice process by providing a yardstick for measuring the fairness of prices.

The SBR model has both similarities and differences relative to the MBR model. First, similar to the MBR model, we expect that a loss, relative to the reference value, decreases utility ($\beta_L < 0$), and that a gain, relative to the reference value, increases utility ($\beta_G > 0$). Again, similar to the MBR model, prospect theory predicts that the absolute value of β_L will exceed the absolute value of β_G because losses are perceived to be more important than gains. Second, unlike the MBR model, the SBR reference price value is not brand specific. This characteristic of the SBR reference price leads to statistical identification issues that prevent the inclusion of a current price variable P in the utility specification (Briesch et al. 1997). In addition, Hardie et al. (1993) argue on conceptual grounds that current price is not needed because only the consumer's comparison to the price of the anchor brand is psychologically meaningful.

Structural heterogeneity

It is important to be able to empirically classify consumers into the three price response segments solely on the basis of observed product choice histories. For this purpose, we make use of the latent class structural heterogeneity methodology developed by Kamakura et al. (1996). The methodology yields both estimates of segment level parameters and posterior probabilities indicating the likelihood that each consumer belongs to each price response segment.

The method is implemented by first constructing three likelihood expressions for each consumer, one corresponding to each of the price response models. Define the log-likelihood of consumer h for price response model s as

$$\mathrm{LL}(h|s) = \sum_t \sum_j Y_{hjt} \log[Pr(j|t, h, s)], \tag{8}$$

where Y_{hjt} is a binary (0–1) indicator variable that equals 1 if the consumer buys brand j at time t, and the time subscript t runs over the consumer's entire choice history. Here, the expression $\Pr(j|t, h, s)$ denotes the probability that consumer h buys brand j at time t, given membership in reference price segment s. That is, $\Pr(j|t, h, s)$ corresponds to the choice probability expressions shown earlier in Eqs. (2), (4) and (7).

Using Eq. (8), we can then write the structural model log-likelihood as

$$\mathrm{LL} = \sum_h \log\left[\sum_s \pi_s \exp[\mathrm{LL}(h|s)]\right], \tag{9}$$

where π_s is interpreted as the overall proportion of consumers who may be described using price response model s. Maximization of (9) yields maximum likelihood estimates of price response segment parameters and sizes. Once these parameters are found, we can define the posterior probability that consumer h follows price response model s as

$$\mathrm{POST}(h, s) = \frac{\pi_s \exp[\mathrm{LL}(h|s)]}{\sum_s \pi_s \exp[\mathrm{LL}(h|s)]}. \tag{10}$$

We use these posterior probabilities in our empirical work to analyze factors that impact consumer encoding of price information.

Past work in the reference price literature has also used latent class methodology to understand household differences in response to price (see, e.g., Briesch et al. 1997; Mazumdar and Papatla 2000). Recently, Erdem et al. (2001) argued against the use of latent class analysis because reference price effects may be difficult to detect as a latent class procedure assigns consumers to segments. We address this issue in two ways. First, by using a loyalty variable in the model specification of each segment, we force the latent class model to place consumers into segments on the basis of response to marketing mix elements—not on the basis of long-run brand preference. Second, by constraining each segment to follow a different pricing rule, we require that consumers be placed into one of only three segments, each of which is characterized by a different way of encoding price information. The fact that each segment has a distinct, non-nested parametric representation (implying a multimodal parameter distribution) increases the likelihood that latent class analysis will perform well in recovering the true heterogeneity in the consumer price mechanism (Andrews et al. 2002). As we show subsequently in our empirical work, these features of the structural heterogeneity approach lead to a clear understanding of the reference price characteristics of the consumer population.

Empirical analysis

We apply the general model in a study of the toilet tissue product category. Our analysis proceeds in two steps. First, we fit the structural heterogeneity model to purchase histories from a consumer scanner panel. Second, we use the posterior probabilities of price segment membership to conduct a price elasticity analysis. We find clear evidence that consumers use reference values to encode price information prior to making a choice decision. Moreover, we find strong evidence that the sensitivity to marketing mix elements is linked to the reference price mechanism used by the consumer.

Data description

The analysis presented here is based upon the toilet tissue purchase records of 341 households from an A.C. Nielsen consumer panel in the Sioux Falls, South Dakota area. A total of 114 weeks are used in this study. The first 39 weeks were used to initialize loyalty variables and memory-based reference prices. (These weeks were also used to compute purchase behavior indices for an analysis of correlates of

Table 1
Toilet tissue brand summary

	Market share	Price	Feature index	Display index
Charmin	32.4	1.15	.23	.22
Northern	32.1	1.12	.23	.14
Cottonelle	20.8	1.13	.32	.17
White Cloud	7.5	1.23	.19	.41
Family Scott	7.3	.98	.25	.19

Note. Market share is measured in terms of units purchased and shown as a percentage. Price is expressed in dollars per 4,000 sheets. The feature and display indices are averages over dummy variables representing each brand's promotional status.

segment membership.) The second 52 weeks were used for model calibration. The last 23 weeks were used for model validation as a holdout sample.

Five brands—Charmin, Northern, Cottonelle, White Cloud, and Family Scott—were selected for analysis, each of which has a brand share bigger than 5 percent (Table 1). These five brands account for 83 percent of the total purchase occasions. During the whole period, 119,613 purchase occasions occur in the product category. Families that make fewer than seven purchases are excluded because estimation of the loyalty variables is not reliable. Additionally, for these light purchasers, reference price estimation would be unreliable as well due to long interpurchase times. A systematic sample of the remaining households yielded a sample of 341 families. To prevent heavy purchasers of the category from dominating the results of the analysis, no more than ten purchase events from the choice history of each household are used during model calibration.

Variable definitions

Most variables in the model are defined in a manner similar to scanner data choice models in the marketing literature. Price is operationalized as price net of coupon when the brand is chosen and as shelf price when the brand is not chosen. Using this same definition, memory-based reference price (IRP in Eq. (5)) is a function of past prices. Feature and display indices are binary (0–1) variables indicating the presence or absence of feature and display conditions during the purchase occasion.

Following Guadagni and Little (1983), we define the set of loyalty variables as

$$\mathrm{LOY}_{hjt} = \rho \mathrm{LOY}_{hj(t-1)} + (1-\rho) Y_{hj(t-1)} \tag{11}$$

where Y_{hjt} is a binary (0–1) variable which equals one when consumer h buys brand j at time t. The smoothing parameter ρ, which is estimated simulated simultaneously with other parameters in the model, is constrained to lie between zero and one. We assume that this parameter is the same for each of the three reference price segments.

This formulation of the loyalty variable permits baseline preferences to vary dynamically over time. It also allows for differences in preferences across households within a particular price response segment. Arguments presented in Bucklin et al. (1998) make it clear that heterogeneity in logit model brand intercepts across brands and consumers leads to heterogeneity in own-price elasticities across brands and consumers. This occurs despite the lack of an explicit model for heterogeneity in market response parameters over consumers within each price response model. For this reason, the model specification used in this analysis is considerably more general than is apparent upon first inspection.

Price endogeneity

A major concern in pricing research is endogeneity in the price variable. Price endogeneity can arise if consumers time their purchases in the category to correspond to favorable pricing conditions (such as low price of a favorite brand or the availability of a coupon for a certain brand). Recently, Chang et al. (1999) argued that some reference price effects reported in the marketing literature are artifacts of price endogeneity. These concerns are particularly relevant in our study because we define price as the shelf price net of any coupons. For these reasons, it is essential that we estimate model parameters in a manner that adjusts for the potential endogeneity of price.

The proper treatment of endogeneity in choice models has received considerable attention recently (Chintagunta 2001; Villas-Boas and Winer 1999). It can be shown that the instrumental variables approach often used in linear regression systems *does not* properly correct for endogeneity in a nonlinear function such as the logit model (Davidson and MacKinnon 1993). For this reason, we employ a control variable approach in correcting the model for potential endogeneity in price (Blundell and Powell 2003; Petrin and Train 2002).

To implement this procedure, we first model each price variable as a first order autoregressive AR(1) process. This AR(1) model is used to forecast the price variable at each time point. Using these forecasts, we obtain the residual (actual minus predicted) at each time point. This residual, which we denote as Correction for Price Endogeneity in our table of parameter estimates, is then placed in the model of each pricing segment as an additional variable. The theory underlying the control variable approach indicates that a significant non-zero coefficient on a residual variable signals the presence of endogeneity in the data. Moreover, the coefficients on the potentially endogenous variables (i.e., price) will be consistent, given the presence of the residual variables.

Structural heterogeneity model

As noted earlier, we assume that each consumer uses only one of the three distinct price response models: the NRP model, the MBR model, or the SBR model. We begin our analysis by considering the evidence for heterogeneity in the pricing mechanism across consumers. In Table 2, we compare the fit of the structural heterogeneity model with three

Table 2
Model comparison

Reference price model	Calibration Sample		Holdout Sample	
	LL	BIC	LL	BIC
NRP	−2925.97	5931.34	−2255.30	4586.51
MBR	−2874.64	5852.51	−2249.78	4605.83
SBR	−2848.20	5783.75	−2216.48	4516.46
Structural heterogeneity (NRP, MBR, SBR)	−2638.91*	5531.94*	−1992.25*	4227.41*

Note. NRP, no reference price; MBR, memory-based reference price; and SBR, stimulus-based reference price. The table displays the log-likelihood (LL) and the Bayesian Information Criterion (BIC) for each model in both the calibration and the holdout datasets. The best model has the *largest* LL value and the *smallest* BIC value. The symbol asterisk (*) denotes the best model in each column.

alternative model specifications, each of which assume that only one pricing rule (NRP, MBR, or SBR) is used by all consumers. Model fit statistics both in the calibration sample and in the holdout sample, strongly favor the structural heterogeneity model. For this reason, we only discuss the structural heterogeneity model results below.

In interpreting the results presented below, it is important that households be clearly assigned to particular reference price segments. As noted earlier, we assume that each consumer only belongs to one segment. Nevertheless, in any empirical work, there will always be some uncertainty about the identity of the segment to which a particular consumer belongs. Following standard latent class procedures, we use model parameters to compute the segment membership probabilities for each consumer (Eq. (10)) and then allocate the consumer to the reference price segment with the highest probability (Wedel and Kamakura 2000). Consistent with Eq. (10), consumers are allocated to segments depending upon both the relative size of the segments and the consumer's observed brand purchase history.

In Table 3, we examine the stability of this process by comparing segment assignments based upon the calibration dataset and with segment assignments based upon the holdout dataset. Perfect consistency in assignment implies that all consumers will fall along the diagonal of the table. We find a statistically significant association in this table with 87 percent of consumers being assigned to the same segment in both datasets. This stability implies that the latent class analysis is successful in unambiguously classifying the vast majority of consumers.

Table 3
Stability of segment classification

Calibration sample	Holdout sample		
	NRP	MBR	SBR
NRP	23 (79%)	2 (7%)	4 (14%)
MBR	10 (7%)	130 (88%)	8 (5%)
SBR	10 (6%)	10 (6%)	144 (88%)

Note. NRP, no reference price; MBR, memory-based reference price; and SBR, stimulus-based reference price. The table compares segment classification of each household using both calibration data and holdout data. Percentages sum to 100 percent within each row. The relationship in the table is statistically significant at the .0001 level. Overall, 87 percent of households are allocated to the same segment in both datasets.

Model parameters

The parameters of the structural heterogeneity model are presented in Table 4. These coefficients are obtained by maximizing the likelihood in Eq. (9). It should be noted that all parameters, including the loyalty smoothing parameter ρ (Eq. (11)) and the MBR reference price smoothing parameter λ (Eq. (5)), are estimated simultaneously. Our algorithm makes use of a procedure developed by Fader et al. (1992) for the estimation of nonlinear parameters in logit models. Accordingly, all parameters presented in Table 4 are maximum likelihood estimates.

A number of results should be noted. There is strong evidence that reference price theory is a better description of the choice process than the classical NRP model. Only 9 percent of the households are classified as NRP. Of the remainder, there are slightly more SBR consumers than MBR consumers. Substantively, we can conclude that the vast majority of consumers in our data follow some sort of reference price mechanism in their choice behavior.

Model coefficients measuring price and promotion response are all in accord with marketing theory. Coefficients for shelf price (found only in the NRP and MBR segments) are negative; feature and display coefficients are positive. Within the MBR segment, we find that the smoothing parameter for internal reference price is quite large ($\lambda = .790$), suggesting that MBR consumers rely upon a considerable amount of past experience in forming price expectations. Moreover, the pattern of the loss and gain coefficients in the MBR and SBR segments conforms to prospect theory. As expected, loss coefficients are negative, gain coefficients are positive, and (within each segment) the absolute value of the loss coefficient exceeds the absolute value of the gain coefficient. The reader is cautioned that a direct comparison of price coefficients across models is not meaningful due to differences in the pricing mechanism across segments. Later, we develop segment-level estimates of price elasticities to permit this sort of comparison.

We also present the coefficients on the Correction for Price Endogeneity variable at the bottom on Table 4. We obtain statistically significant results only in the NRP segment. Again, we stress that the evidence for price endogeneity does not invalidate the parameter estimates for price and promotion. The control variable approach to endogeneity correction

Table 4
Structural heterogeneity model estimates

	Segment		
	NRP	MBR	SBR
Brand preference			
Charmin	–	–	–
Northern	0.249 (0.292)	−0.584** (0.101)	−0.376** (0.097)
Cottonelle	2.198** (0.252)	−0.582** (0.104)	−0.498** (0.103)
White Cloud	0.684+ (0.366)	−0.814** (0.151)	−0.347* (0.157)
Family Scott	−1.035* (0.463)	−3.635** (0.233)	−1.555** (0.191)
Loyalty	0.406** (0.121)	0.430** (0.052)	1.003** (0.050)
Loyalty smoothing parameter (ρ)	0.890** (0.112)	0.890** (0.112)	0.890** (0.112)
Price effects			
Price	−6.695** (1.430)	−10.424** (0.799)	–
Loss	–	−4.179** (1.128)	−18.712** (1.238)
Gain	–	0.857* (0.410)	1.037+ (0.604)
Reference price smoothing parameter (λ)	–	0.790** (0.248)	–
Promotion effects			
Feature	0.510 (0.446)	2.603** (0.230)	0.918** (0.220)
Display	2.029** (0.386)	3.577** (0.254)	1.394** (0.211)
Correction for price endogeneity	4.214* (2.023)	0.749 (0.985)	1.322 (0.996)
Segment proportion (%)	9	43	48

Note. NRP, no reference price; MBR, memory-based reference price; and SBR, stimulus-based reference price. Brand constants for Charmin are set to zero for purposes of model identification. Numbers in parentheses are standard errors.
+ Parameters that are significantly different from zero are denoted for .10 level.
* Parameters that are significantly different from zero are denoted for .05 level.
** Parameters that are significantly different from zero are denoted for .01 level or better.

ensures that all other coefficients in the model are consistent estimates of the true parameters. For this reason, we retain the price endogeneity correction in all segments, regardless of significance level.

Analysis of price elasticities

To obtain insight into the differences among the three segments, we first consider the implications of the model for price sensitivity. For this analysis, we computed segment-level market shares (using the coefficients from Table 4) for each brand under three conditions: the current brand price, 10 percent below the current brand price, and 10 percent above the current brand price. These forecasts were then used to compute the estimates of own price elasticities found in Tables 5 and 6.

Elasticities were calculated using the following procedure. In each of the three pricing conditions (current, 10 percent above, 10 percent below), all competitive brands were kept at their respective current prices. We computed the long-run choice share for each brand and for each consumer by averaging the predicted choice shares across all time points in the consumer's purchase history. To specialize these values to each price response segment (MBR, SBR, or NRP), we allocated each consumer to the most likely segment using the posterior probabilities of Eq. (10). The three choice share fore-

Table 5
Elasticity analysis for price decreases

	10% price decrease			Significance levels for tests of segment differences		
	NRP	MBR	SBR	NRP versus MBR	NRP versus SBR	MBR versus SBR
Charmin	−4.77 (1.31)	−4.92 (1.37)	−2.86 (1.23)	*ns*	.001	.001
Northern	−4.13 (1.51)	−4.84 (1.45)	−3.40 (1.40)	.049	.034	.001
Cottonelle	−2.47 (1.45)	−6.49 (1.63)	−3.67 (1.40)	.001	.001	.001
White Cloud	−4.67 (1.85)	−5.46 (2.12)	−3.99 (1.97)	*ns*	*ns*	.001
Family Scott	−3.31 (1.20)	−4.62 (1.45)	−1.40 (0.87)	.001	.001	.001
Brand average	−3.87 (0.57)	−5.26 (0.70)	−3.06 (0.67)	.001	.001	.001

Note. NRP, no reference price; MBR, memory-based reference price; and SBR, stimulus-based reference price. The left-hand side of the table displays own-price elasticity means and standard deviations (in parentheses) predicted by the structural heterogeneity model in response to a 10 percent decrease in price. The row denoted brand average is the mean of all elasticities within a particular segment. The right-hand side of each table displays the significance levels of the Bonferroni multiple comparison test for each brand. Differences that are not significant are denoted as *ns*.

Table 6
Elasticity analysis for price increases

	10% price increase			Significance levels for tests of segment differences		
	NRP	MBR	SBR	NRP versus MBR	NRP versus SBR	MBR versus SBR
Charmin	−6.04 (2.50)	−5.91 (2.22)	−4.06 (2.10)	*ns*	.001	.001
Northern	−4.50 (2.22)	−4.92 (1.93)	−3.98 (1.92)	*ns*	*ns*	.001
Cottonelle	−5.25 (2.49)	−7.26 (2.13)	−6.04 (2.24)	.000	*ns*	.001
White Cloud	−5.22 (2.75)	−6.01 (2.60)	−3.58 (2.01)	*ns*	.002	.001
Family Scott	−4.42 (1.93)	−4.57 (1.75)	−2.19 (1.40)	*ns*	.001	.001
Brand average	−5.09 (1.02)	−5.73 (0.91)	−3.97 (0.92)	.002	.001	.001

Note. NRP, no reference price; MBR, memory-based reference price; and SBR, stimulus-based reference price. The left-hand side of the table displays own-price elasticity means and standard deviations (in parentheses) predicted by the structural heterogeneity model in response to a 10 percent increase in price. The row denoted brand average is the mean of all elasticities within a particular segment. The right-hand side of each table displays the significance levels of the Bonferroni multiple comparison test for each brand. Differences that are not significant are denoted as *ns*.

casts for each brand allow us to determine own-price arc elasticities: the observed percentage change in the consumer's choice share divided by the percentage change in price.

Each elasticity in Tables 5 and 6 is the average own price elasticity for all consumers within a particular reference price segment. Using standard ANOVA procedures, we found that means are significantly different ($p < .001$) across segments for each brand (and for the overall brand average) in both tables. The results of a Bonferroni multiple mean comparison analysis can be found on the right-hand side of each table.

A clear pattern emerges by studying the results. Differences in own price elasticities across the two segments using reference price (MBR and SBR) follow a simple rule: MBR consumers are more price sensitive than SBR consumers. This pattern holds true both for price increases as well as price decreases. On average (with some exceptions for particular brands), NRP consumers represent the middle of a price sensitivity continuum with MBR and SBR consumers at the opposite ends of the scale. (This explains, in part, why some of the comparisons of the NRP segment with other segments are not statistically significant.) Thus, the reference price mechanism used by a consumer has a very clear correspondence to heterogeneity in price sensitivity in the consumer population.

Correlates of segment membership

To further understand the differences in price sensitivity across segments, we developed general indicators of buying behavior that could be observed by a retailer with access to panel data. We examined average price paid, the intensity of brand switching, and promotional conditions (coupon, feature, and display) during a purchase. The brand-switching index is defined as the proportion of times the brand purchased at time t was different from the brand purchased at time $t-1$. The promotional indices (for feature, display and coupon) can be interpreted as the proportion of times a consumer purchased in the category when the given promotional variable was present for the selected product. Because all variables are constructed using only the initialization period of the dataset, our analysis does not confound the estimation of the structural heterogeneity model with the measurement of consumer purchase characteristics.

The profile of these consumer characteristics across the three price response segments is presented in Table 7. The segment means are computed by using the calibration data to assign each consumer to the segment with highest posterior membership probabilities (Eq. (10)). To test the differences in means across groups, we used standard ANOVA procedures based upon these segment assignments. This test yielded evidence for statistically significant differences ($p < .001$) across the price segment means for all variables. The results of a Bonferroni multiple mean comparison analysis can be found on the right-hand side of Table 7.

Although we do not make formal predictions for each variable in Table 7, our general expectation is that the rank order of means should parallel the findings in the price elasticity analysis. Since the MBR and SBR appear to be at different

Table 7
Correlates of segment membership

	Price segment means			Significance levels for tests of mean differences		
	NRP	MBR	SBR	NRP versus MBR	NRP versus SBR	MBR versus SBR
Average price paid (Dollars)	.982 (.225)	.949 (.383)	1.010 (.419)	*ns*	*ns*	.012
Brand switching index	.584 (.144)	.627 (.282)	.493 (.251)	*ns*	.100	.001
Coupon usage	.272 (.086)	.298 (.186)	.236 (.170)	*ns*	*ns*	.054
Buy on feature	.203 (.064)	.304 (.182)	.227 (.148)	*ns*	*ns*	.001
Buy on display	.173 (.078)	.195 (.139)	.121 (.101)	*ns*	*ns*	.001

Note. Left-hand side of table displays segment means and (in parentheses) standard deviations. All variables are derived from the initialization data period—not the calibration data period. The right-hand side of the table displays the significance levels of a Bonferroni multiple mean comparison test for each variable. Differences that are not significant are denoted as *ns*.

ends of a price sensitivity scale, we should expect to find clear differences between the MBR and SBR groups with a rank order of means consistent with the notion that the pricing environment plays a more important role in choice for MBR consumers. In fact, this expectation is confirmed by the results in Table 7. All means are statistically different between the MBR and SBR segments. Relative to SBR consumers, MBR consumers pay lower prices, switch brands more often, use more coupons, and buy more frequently under feature and display conditions. Moreover, with the exception of the buying on feature variable, the means of the NRP segment fall in between the means of the MBR and SBR segments, consistent with the idea that the NRP segment is in the middle of a price sensitivity scale.

Understanding reference price behavior

The reference price segment profiles presented above do not address why the use of a different reference price mechanism translates into differences in price sensitivity. We argue that the differences in MBR and SBR consumers are directly related to the way that consumers use price information in making a decision. For the MBR consumer, considerable cognitive resources are devoted to remembering past prices and using this information for the current choice. This strongly suggests that MBR consumers continually monitor the pricing environment and condition their behavior on changes in this environment. Moreover, because a brand's current reference price depends upon its previous price, MBR consumers have a tendency (due to loss aversion) to switch away from brands that were promoted on the last purchase occasion. The pattern of the MBR means in Table 7 is clearly consistent with this behavioral description.

In contrast, SBR consumers approach the pricing environment in a very different manner. As noted earlier, SBR consumers remember the identity of the last brand purchased, not the set of past prices. They then use the current price of this reference brand to determine the fairness of the prices currently in the store. Due to loss aversion, the SBR consumer will assign considerable disutility to brands priced above the reference brand. In practice, this process will tend to focus the consumer's attention on a subset of brands—in effect, restricting the consumer's current choice set to only those brands with sufficiently low prices. Because the SBR segment does not continually monitor the pricing environment and restricts the size of the choice set at the point of purchase, we would expect a relatively less price sensitive consumer who does not routinely take advantage of retailer promotions. This logic is consistent with the pattern of SBR means found in Table 7.

Summary

The central message of our analysis of the toilet tissue category is that most consumers encode prices in some fashion. MBR consumers, who recall prices from memory, are the most price and promotion responsive because they continually monitor the pricing environment. SBR consumers, who focus on the identity of the brand that was previously purchased, are least price sensitive because they do not monitor the pricing environment. We believe that these SBR consumers account for a significant proportion of those who do not remember purchase prices, as revealed by the work by Dickson and Sawyer (1990). Accordingly, all reference price consumers are not inherently price sensitive. It depends upon how reference prices are formed and how reference prices are used by the consumer to make a purchase decision.

Conclusions

The goal of this study is to understand how consumers encode price information in making a choice decision. We identify three types of price response consumers (no reference price, memory-based reference price, and stimulus-based reference price) and describe a methodology that permits consumers to be classified into price response segments using scanner panel choice histories. We examine correlates of these segments in terms of both consumer purchase characteristics and price elasticities. Substantively, we find that the tendency to use past prices in making a choice is associated with higher sensitivity to price.

Psychology of price

This study makes the interesting theoretical point that simple choice models (represented by the NRP price response model) are apt to be inadequate descriptions of the manner in which price impacts the purchase decision. Of all the models considered in this study, the NRP price response process is most representative of economic models of consumer choice. In fact, it is possible to derive the NRP model by assuming that consumers maximize utility subject to a budget constraint. Accordingly, price enters the NRP model without any modification because nominal price provides sufficient information for the rational consumer to determine optimal expenditures. The fact that only 9 percent of the consumers in our study follow the NRP model suggests that the economic framework is missing an important element of consumer decision-making.

In contrast, the MBR and SBR models—both of which are based on the psychology literature—argue that price plays a dual role in brand choice: as a constraint on behavior and as a cue about the fairness of the offer made by the retailer. Prices that are viewed as inappropriate, either because they are too high relative to past prices (MBR) or too high relative to the current price of a focal brand, generate a psychological reaction that adds substantial disutility to the brand under consideration. Viewed in this manner, it is not at all surprising to find that the majority of consumers use reference price information, and consumer differences in price sensitivity are linked to the type of reference price mechanism used for purchase decisions. The performance of the reference price models in our study provides a strong argument for the inclusion of psychological constructs in choice models.

Managerial implications

From a managerial perspective, the findings of this study suggest that retailer pricing strategy is dependent upon how consumer process price information. When consumers follow a stimulus-based model, price comparisons are centered on the current price of a reference brand. When consumers follow a memory-based (internal) model, price comparisons are focused on past prices of the brand under consideration. Although retailers cannot directly control the process that consumers use to form reference prices, they can indirectly control reference prices by manipulating the price pattern that consumers see (Greenleaf 1995; Kopalle et al. 1996). Consider the case of a retailer following a HI-LO price format. We would expect that frequent promotions would create an alternating pattern of positive and negative impacts for MBR consumers (due to perceived gains and losses over time). The impact of these promotions on the SBR consumer depends on the depth of the discount; only those promotions that generate prices below the price level of the focal brand will have an effect. In contrast, an EDLP retailer minimizes the gain/loss mechanism of MBR consumers due to infrequent promotions. However, by choosing the price points of the product category assortment carefully, the same EDLP retailer can ensure that all SBR consumers have a variety of products with reasonable prices, regardless of the identity of the focal brand.

Because our study is focused on exclusively on brand choice, we cannot directly measure the impact of reference price behavior on store traffic generation. However, this work suggests the possibility that price promotions can increase store traffic by appealing to the MBR segment of the retailer's consumer base. One way this might be done is to alternate promotions on two high-preference brands in a product category. For MBR consumers, this provides a time pattern of perceived gains for at least one brand in the category at each time point. Because MBR consumers continually monitor the pricing environment, promotions are likely to be noticed and have the potential of impacting store choice. In contrast, because SBR consumers do not appear to monitor the pricing environment, promotions are unlikely to have a substantial impact on store choice. For these consumers, promotions may serve instead to increase store loyalty by providing occasional brand purchases that are perceived as excellent values.

Model extensions

The work reported here could be generalized in a number of ways. The approach could be replicated across different product categories to determine the generality of the reference price profiles reported here. Implicitly, this would examine the stability of the price response mechanisms across categories. It would also be worthwhile to investigate consumer heterogeneity in price response in the context of a category purchase incidence model. Recently, Bell and Bucklin (1999) investigated the role of internal reference points in category purchase decisions. This work could be extended by predicting category incidence using a nested logit framework incorporating each of the three price response models reported in this research. By combining a multiple-category perspective with a category incidence construct, we would have the key components for a general model linking reference price behavior to store choice.

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