Ronald W. Niedrich, Danny Weathers, R. Carter Hill, and David R. Bell

To construct a price judgment, consumers compare a focal price with one or more reference prices. However, reference price operationalizations in the brand choice literature use single-point summary measures that cannot account for several distributional effects. To account for effects beyond the first moment of the reference price distribution, the authors specify price judgments in models of brand choice in accordance with range–frequency theory. The findings indicate that range–frequency price judgments provide a more complete specification of reference price effects and become more important with an increase in the second and third moments of a reference price distribution. The data also indicate that range effects are stronger for coupon users and frequency effects are stronger for consumers exposed to a trend of prices. The results have several implications for choice modeling, pricing theory, and pricing strategy.

Keywords: consumer price judgments, brand choice, range–frequency theory, reference prices, mixed multinomial logit models

Specifying Price Judgments with Range–Frequency Theory in Models of Brand Choice

Approximately 38% of all purchases of consumer goods in the United States occur during a price promotion (Steenkamp et al. 2005). These temporary discounts result in bimodal and negatively skewed price distributions over time (Rao, Arjunji, and Murthi 1995). Although it is well known that discounts affect reference prices and subsequent brand choice, the distributional effects of reference prices on brand choice are less clear. Brand choice models currently operationalize reference price using a single-point summary measure of the price distribution, typically the central tendency (Mazumdar, Raj, and Sinha 2005). However, behavioral research has demonstrated that central tendency models are unable to account for the effects of reference price distribution range, modality, and skewing on consumer price perceptions in the laboratory (e.g., Janiszewski and Lichtenstein 1999; Niedrich, Sharma, and Wedell 2001). Thus, although extant models capture central tendency effects, they are unable to account for the impact of the reference price distribution beyond the first moment.

To account for distributional effects, we specify reference prices in accordance with range–frequency theory (Parducci 1965). We then develop operational procedures that allow for the use of range–frequency theory in models of brand choice. Next, we test the approach using scanner panel data from three product categories. Finally, we extend our understanding of reference price effects by advancing two additional research questions: (1) When is it important to employ range–frequency theory? and (2) What factors affect the relative influence of range versus frequency effects?

This research provides the following new contributions to the literature on reference price effects in consumer brand choice behavior. First, range–frequency theory improves the model fit over current models and allows for a more complete specification of reference price effects.

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1We thank the editor and an anonymous reviewer for suggesting these lines of inquiry.
Second, the importance of employing range–frequency theory increases with the second and third moments of a reference price distribution and therefore is particularly relevant to environments in which price volatility is the norm. Finally, range effects are stronger for coupon users, and frequency effects are stronger for consumers who have been exposed to a trend of prices over time. These findings have important implications for choice modeling, pricing theory, and pricing strategy, which we explicate in the “General Discussion” section.

**BASE UTILITY MODEL**

Consistent with previous reference price research (e.g., Briesch et al. 1997; Mazumdar and Patapta 2000), we define the base utility model as the utility of brand j for household h on purchase occasion t (U_{base, jht}) as follows:

\[ U_{base, jht} = \beta_{pj} + \beta_{dj}(price_{jht}) + \beta_{dj}(display_{jht}) + \beta_{lj}(loyalty_{jht}) + \epsilon_{jht}, \]

where \( price_{jht} \) is the price of j for h at t, \( display_{jht} \) is 1 if j is on display at t and 0 if otherwise, \( feature_{jht} \) is 1 if j is featured at t and 0 if otherwise, and \( loyalty_{jht} \) is a measure of brand loyalty. We use Guadagni and Little’s (1983) operationalization of brand loyalty:

\[ loyalty_{jht} = \delta(loyalty_{jht}^{(t-1)}) + (1-\delta)(I_{jht}^{(t-1)}), \]

where \( \delta, 0 < \delta < 1 \), is the carryover parameter and \( I_{jht}^{(t-1)} \) is equal to 1 if brand j was purchased by household h at occasion \( t-1 \) and 0 if otherwise. The direction of the effects for the variables in Equation 1 is well established in the literature (e.g., Briesch et al. 1997; Mazumdar and Patapta 2000). In particular, we expect \( loyalty_{jht} \), \( display_{jht} \), and \( feature_{jht} \) to have positive effects and \( price_{jht} \) to have a negative effect on \( U_{base, jht} \). Next, we discuss models of price judgments.

**PRICE JUDGMENTS**

Price judgments reflect the process by which consumers interpret price information and can influence consumer decisions such as what, when, where, and how much to buy (Gupta 1988). To construct a price judgment, consumers compare a focal price with one or more reference prices (e.g., price–reference price; Blattberg, Briesch, and Fox 1995; Kalyanaram and Winer 1995). As price judgments increase, they appear less attractive and have a negative effect on choice. Because direct measures of consumer price judgments are not available in scanner panel data, brand choice models include estimates of these judgments based on brand prices that are available in the data.

The brand choice literature supports two generalizations about the effect of price judgments. First, choice models that include a price judgment have a significantly better fit than base utility models that include only the focal price (Briesch et al. 1997; Lattin and Bucklin 1989; Rajendran and Tellis 1994). Second, to reflect the notion that consumers may use multiple reference price categories in constructing price judgments (Kalyanaram and Winer 1995; Winer 1988), inclusion of estimates for both a memory-based price judgment and a stimulus-based price judgment improves the model fit over a single reference price model (Mayhew and Winer 1992; Mazumdar and Patapta 2000; Rajendran and Tellis 1994). Consequently, we investigate price judgments in both memory-based and stimulus-based reference price contexts.

The literature reveals considerable variability in the way reference price effects are captured because models have been developed more empirically than theoretically (Bell and Lattin 2000). In testing several alternative reference price models, Briesch and colleagues (1997) report the best stimulus-based and memory-based operationalizations, which we employ as baselines against which to test range–frequency theory. These baseline models employ a single-point summary measure of the reference price distribution.

**Baseline Price Judgments**

**Stimulus-based choice context.** Stimulus-based price judgments are the result of comparisons of the current price of the focal brand with other prices in the external environment, sometimes referred to as “external reference prices” (Mazumdar, Raj, and Sinha 2005). Briesch and colleagues (1997) report that the best formulation of external reference prices is given by the current price of the reference brand (Hardie, Johnson, and Fader 1993). The logic behind this approach is that consumers may use the previously purchased brand as the status quo option and therefore are more likely to attend to the current shelf price of this alternative in judging the focal brand price. Thus, the baseline price judgment in the stimulus-based choice context is given by the following:

\[ \text{Price Judgment}_{stim, jht} = price_{jht} - price_{[cb(t-1)]ht}, \]

where \( price_{[cb(t-1)]ht} \) is the shelf price on purchase occasion t of the brand chosen by household h on the previous purchase occasion \( [cb(t-1)] \).

**Memory-based choice context.** Memory-based price judgments are the result of comparisons of the current price of the focal brand with historical prices of the focal brand that are accessible in memory, sometimes referred to as “internal reference prices” (Mazumdar, Raj, and Sinha 2005). Briesch and colleagues (1997) report that the best formulation of internal reference prices is given by the brand-specific exponentially weighted model (Kalyanaram and Little 1994; Lattin and Bucklin 1989). This specification captures the temporal effect because it gives more weight to more recent prices. Thus, the baseline price judgment in the memory-based choice context is given by the following:

\[ \text{Price Judgment}_{mem, jht} = price_{jht} - IRP_{jht}, \]

\[ IRP_{jht} = (1 - \alpha)(IRP_{jht}^{(t-1)}) + \alpha(price_{jht}^{(t-1)}), \]

where \( \alpha, 0 < \alpha < 1 \), is the carryover parameter and \( price_{jht}^{(t-1)} \) is the shelf price of brand j observed by household h on occasion \( t-1 \) for the internal reference price \( IRP_{jht} \). Estimates of \( \alpha \) reported in the literature range from .2 to .8, suggesting that between 2 and 20 historical prices are used in the price judgment task.

**Range–Frequency Price Judgments**

To account for effects beyond the reference price distribution’s first moment, we employ range–frequency theory (Parducci 1965, 1995), which asserts that the judged value of a stimulus is determined by two contextual principles. According to the range principle, judgments reflect the location of the focal stimulus relative to the most extreme
values defining the relevant judgment context. According to the frequency principle, the location of the focal stimulus is described by its rank within this context. As Equation 5 shows, the subjective judgment \( J \) of stimulus \( i \) in context \( k \) is conceived as a compromise between the range, \( R \), and the frequency, \( F \), principles, in which the weighting parameter, \( w \), is a value between zero and one:

\[
J_{ik} = (w)R_{ik} + (1 – w)F_{ik}.
\]

We define the range value of price \( i \) in reference price context \( k \), \( R_{ik} \), as the proportion in Equation 6, where \( S_{ik} \) is the subjective value of price \( i \). \( S_{\text{min},k} \) is the subjective value of the minimum price in \( k \), and \( S_{\text{max},k} \) is the subjective value of the maximum price in \( k \). We define the frequency value, \( F_{ik} \), as the proportion in Equation 7, where \( \text{Rank}_{ik} \) is the rank of price \( i \) in \( k \), 1 is the minimum rank, and \( N_k \) is the total number of prices in \( k \) (Parducci 1995):

\[
R_{ik} = (S_{ik} – S_{\text{min},k})/(S_{\text{max},k} – S_{\text{min},k}), \quad \text{and}
\]

\[
F_{ik} = (\text{Rank}_{ik} – 1)/(N_k – 1).
\]

Figure 1 illustrates the differences between range–frequency theory and a central tendency model. In Figure 1, predicted price judgments are provided for two hypothetical price distributions with the same mean: a normal distribution (top panel) and a negatively skewed distribution (bottom panel). Price judgments are scaled from zero (most attractive) to one (least attractive). Although range–frequency theory predicts that consumer price judgments will reflect some compromise between range and frequency effects, we illustrate the effects separately. Note that compared with the top panel, the linear range predictions shift to the left and the nonlinear frequency predictions shift to the right in the bottom panel. Although ranks operationalize frequency effects in Equation 7, a continuous response function can be conceptualized as the cumulative frequency of the underlying distribution of prices, as Figure 1 shows. Because the two distributions have the same mean price, the response function for a central tendency model is the same in these two cases.

**Stimulus-based choice context.** Because it is unclear which brands consumers will attend to on any given purchase occasion, it may not be possible to know with certainty the prices that define the stimulus-based judgment context. However, it seems reasonable to assume that consumers are more likely to notice the shelf prices of brands they have previously purchased. In defining the stimulus-based context, we extend the notion of the reference brand (Hardie, Johnson, and Fader 1993) to a consideration set. That is, we define the reference price context as the current shelf prices of all brands previously purchased by the household. Consequently, the range–frequency (RF) price judgment in the stimulus-based choice context is as follows:

\[
\text{Price Judgment}_{\text{RF}, \text{stim}, j} = (w)(\text{price}_{j} – \text{price}_{\text{min}})/\left(\text{price}_{\text{max}} – \text{price}_{\text{min}}\right) + (1 – w)(\text{rank}_{j} – 1)/(N_{\text{set}} – 1),
\]

where the stimulus-based judgment context is defined as the consideration set of prices, \( s \), \( \text{price}_{\text{min}} \) is the minimum brand price in set \( s \) for household \( h \) on occasion \( t \), \( \text{price}_{\text{max}} \) is the maximum price in set \( s \) for household \( h \) on occasion \( t \), \( \text{rank}_{j} \) is the rank of brand \( j \)’s price in set \( s \) for household \( h \) on occasion \( t \), and \( N_{\text{set}} \) is the number of brands in the consideration set for household \( h \) on occasion \( t \).

**Memory-based choice context.** Again, the set of prices that define the judgment context is a critical assumption. In the laboratory, the memory-based judgment context is defined by all prices presented to respondents during the experiment (e.g., Niedrich, Sharma, and Wedell 2001; Parducci and Wedell 1986). However, it is unclear how far back in time consumers recruit historical prices in a memory-based judgment task. Although \( \alpha \) in the exponentially weighted model suggests a time frame, consumers may recruit more salient prices encoded farther back in time than suggested by \( \alpha \), such as extreme or frequent prices that influence range and frequency effects. Consequently, as with \( \alpha \), the optimal time interval needed to capture memory-based range and frequency effects must be determined empirically. Thus, the range–frequency model for memory-based price judgments is as follows:

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Notes: We show predicted price judgments (higher values are less attractive) in response to a normal (top panel) and a negatively skewed (bottom panel) distribution of prices with the same mean. Range–frequency theory predicts some compromise between the range and the frequency response functions, which are illustrated separately. A central tendency model predicts no difference between price judgments in these two cases.

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2To test our operationalization of the stimulus-based judgment context, we compared the fit of the choice models using the consideration set described here with the same models using the prices of all available brands on occasion \( t \). In all cases, the consideration set approach leads to a better model fit, as reflected in larger log-likelihoods.
Factors Affecting Range–Frequency Price Judgments

Although H1 is our primary focus, we advance our understanding of reference price effects by investigating two additional research questions. First, when is it important to employ range–frequency theory? That is, what variables moderate the impact of range–frequency price judgments on choice? Second, what factors affect the relative influence of range versus frequency effects? That is, what variables moderate the weighting parameter, w, in constructing range–frequency price judgments?

The prediction for when range–frequency price judgments are relatively more important is straightforward. When a reference price distribution is not well characterized by the first moment (e.g., when the second and third moments are large), a central tendency measure of this distribution will perform poorly in predicting consumer price judgments (Niedrich, Sharma, and Wedell 2001). Accordingly, we expect that the influence of the range–frequency price judgment increases with the variance and skew of the reference price distribution.3

H2: Range–frequency price judgments have a stronger impact on choice when the reference price distribution (a) has higher variance and (b) is more highly skewed.

Several factors, including product attributes, the choice environment, and consumer traits, may moderate the range–frequency weighting parameter (w). First, we investigate the effects of consumer learning and memory. Factors that bias the retrieval of reference prices could affect w. One such factor is the presentation order of brand prices. Because stimulus encoding is episodic (Nosofsky and Zaki 2002), presentation order is linked with price information in memory. Exposure to a trend of prices over time should help the consumer locate the ordinal position of the focal price within the set of reference prices, thus increasing memory-based frequency effects, which depend on the consumer’s ability to rank prices.

H3a: The frequency effect is higher (i.e., w is lower) for consumers who have been exposed to a trend of prices than for those who have not.

Second, we consider coupon proneness (i.e., consumer propensity to use coupons more than other types of discounts), a consumer trait that may affect the weighting parameter in the memory-based choice context. Lichtenstein, Netemeyer, and Burton (1991) find that coupon-prone consumers used internal reference prices less than value-conscious consumers (i.e., those concerned about paying low prices regardless of discount type). A potential explanation for their findings is that coupon users attended to more extreme prices not captured by the internal reference price measure, which more closely aligned with frequency effects than range effects. Because many coupon users associate coupons with feelings of being a “smart shopper” (e.g., Mittal 1994), we conjecture that coupon users will find the endpoints that define the reference price range to be more helpful in maximizing their hedonic goal. Thus, we hypothesize the following:

H3b: The range effect is higher (i.e., w is higher) for consumers who use coupons than for those who do not.

ANALYSIS AND RESULTS

Data

We tested the hypotheses using scanner panel data in three product categories: 32-ounce bottles of ketchup, one-pound packages of stick margarine, and 6.5-ounce cans of light tuna. The data were collected from nine stores across two markets over a 123-week period. We selected for analysis all the brands that were available at all stores on every purchase occasion. Thus, we considered four brands of ketchup (Heinz, Hunt’s, Del Monte, store brand), six brands of margarine (Imperial, Parkay, Blue Bonnet, Fleishmann’s, Mazola, store brand), and four brands of tuna (StarKist–water, StarKist–oil, Chicken of the Sea–water, Chicken of the Sea–oil). The selected brands accounted for 83.9% of all 32-ounce ketchup purchases, 68.1% of all one-pound stick margarine purchases, and 86.9% of all 6.5-ounce light tuna purchases. The ACNielsen data were made available through the University of Chicago’s Graduate School of Business.

For each product category, the data were divided into initialization, estimation, and validation samples, which contained 52, 44, and 27 weeks of data, respectively.4 We employed a “purchase selection rule” by using all purchases of the selected brands (Gupta et al. 1996), and we eliminated “light” users from each category by selecting households that made at least ten purchases of the target brands in that category over the 123-week period, with at least one purchase during each of the initialization, estimation, and validation periods (Han, Gupta, and Lehmann

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3Range–frequency theory maps the location of a price onto a psychological judgment scale that assigns a value between 0 and 1. Thus, summary descriptions of a reference price distribution (e.g., variance and skew) and price judgments (e.g., range and frequency values) are not equivalent concepts.

4The relatively long initialization sample was necessary to determine empirically the time horizon that consumers use in constructing memory-based price judgments.
Utility Model Estimation

To account for heterogeneity across households, we employ mixed multinomial logit models in which the parameters in a linear random utility function are separated into fixed and random components (Hensher and Greene 2003; Train 2003). We assume that household \( h = 1, …, H \) chooses among \( J \) brand alternatives and obtains utility \( U_{hj} = x_{hj} \beta_j + \epsilon_{hj} \) for brand \( j \), where \( x_{hj} \) is a vector of explanatory variables, \( \beta_j \) is a vector of parameters, and \( \epsilon_{hj} \) are i.i.d. extreme value errors. Because households differ in their responses to changes in the covariates as a result of unobserved heterogeneity, the parameters \( \beta_j \) are assumed to vary across households. Given \( \beta_j \), the probability that household \( h \) chooses brand \( j \) is \( P[j|\beta_j] = \exp(x_{hj} \beta_j) / \sum_j \exp(x_{hj} \beta_j) \). We make the standard assumption that response parameters are normally distributed in the population. Specifically, \( \beta_j \) comprises a fixed population mean \( (\bar{\beta}) \) and random components \( (\eta_h) \), so that \( \beta_j = \bar{\beta} + \eta_h \) and \( \bar{\beta} \sim N(0, \Sigma) \). The covariance matrix, \( \Sigma \), allows for correlation among parameters, and the random utility is now \( U_{hj} = x_{hj} \beta_j + \epsilon_{hj} = x_{hj} \beta_j + \epsilon_{hj} \eta_h + \epsilon_{jht} = x_{hj} \beta_j + \eta_h \). The composite error term \( (\epsilon_{hj}) \) is correlated across alternatives through the common stochastic component \( (\eta_h) \), and the independence from irrelevant alternatives assumption is not imposed.

We estimate \( \beta_j \) and the unique elements of \( \Sigma \) that define the density \( f(\beta) \), where \( \Sigma = I \Sigma \). If we assume that the coefficients are uncorrelated, \( \Gamma = \text{diag}(\sigma_1, \sigma_2, …, \sigma_K) \), and \( \sigma_k \) denotes the standard deviation of the marginal density, such that \( \beta_j \sim N(\beta_j, \Sigma) \). The collection of unknown parameters is denoted by \( \theta \), and in the uncorrelated case, \( \theta = (\beta_1, …, \beta_K, \sigma_1, …, \sigma_K) \). Estimation is by maximum “estimated” likelihood, and the log-likelihood is given by \( \ln L(\theta) = \sum_h \ln [\exp(x_{hj} \beta_j) / \sum_j \exp(x_{hj} \beta_j)] \), in which the probabilities \( P_{hj} \) are conditional on \( \beta_j \). We obtain unconditional probabilities by integrating over the heterogeneity distribution so that \( P_{hj}(\theta) = \int \exp(x_{hj} \beta_j) / \sum_j \exp(x_{hj} \beta_j) \). Because this K-dimensional integral has no closed-form solution, the probabilities \( P_{hj}(\theta) \) are approximated through simulation. That is, \( P_{hj}(\theta) = 1/R \sum_k \exp(x_{hj} \beta_j) / \sum_j \exp(x_{hj} \beta_j) \).

Given the density \( \beta \sim N(\bar{\beta}, \Sigma) \), we make random draws \( \beta^r, r = 1, …, R \), where \( R \) is “large.” Our estimations are based on 100 Halton draws (Train 2003). The simulated log-likelihood \( \text{LL}(\theta) = \sum_h \ln [\exp(x_{hj} \beta^r) / \sum_j \exp(x_{hj} \beta^r)] \) is maximized with respect to \( \theta \) by standard numerical optimization procedures. The maximum likelihood estimator \( \hat{\theta} \) is consistent and asymptotically normal, with an estimated asymptotic covariance matrix that is based on the matrix of second derivatives.

Overview of the Analysis

To test \( H_{1a} \), we compare three utility equations in the stimulus-based choice context that differ in the price judgments added to Equation 1 (\( U_{\text{base}, jht} \)). Using “S” to denote “stimulus based,” the first utility specification, S.1, adds the baseline price judgment (Equation 3). The second equation, S.2, adds the range–frequency price judgment (Equation 8). The third utility specification, S.3, adds the baseline price judgment (Equation 3) and the range–frequency price judgment (Equation 8):

(S.1) \( U_{jht} = U_{\text{base}, jht} + \beta_{\text{stim}(G)}(\text{Price Judgment}_{\text{stim}(G), jht}) + \beta_{\text{stim}(L)}(\text{Price Judgment}_{\text{stim}(L), jht}) \)

(S.2) \( U_{jht} = U_{\text{base}, jht} + \beta_{\text{RF, stim}}(\text{Price Judgment}_{\text{RF, stim}, jht}) \)

(S.3) \( U_{jht} = U_{\text{base}, jht} + \beta_{\text{stim}(G)}(\text{Price Judgment}_{\text{stim}(G), jht}) + \beta_{\text{RF, stim}}(\text{Price Judgment}_{\text{RF, stim}, jht}) \)

To test \( H_{1b} \), we compare three utility equations in the memory based choice context that differ in the price judgments added to Equation 1 (\( U_{\text{base}, jht} \)). Using “M” to denote “memory based,” the first utility specification, M.1, adds the baseline price judgment (Equation 4). The second equation, M.2, adds the range–frequency price judgment (Equation 9). The third utility specification, M.3, adds the baseline price judgment (Equation 4) and the range–frequency price judgment (Equation 9):

(M.1) \( U_{jht} = U_{\text{base}, jht} + \beta_{\text{mem}}(\text{Price Judgment}_{\text{mem}, jht}) \)

(M.2) \( U_{jht} = U_{\text{base}, jht} + \beta_{\text{RF, mem}}(\text{Price Judgment}_{\text{RF, mem}, jht}) \)

(M.3) \( U_{jht} = U_{\text{base}, jht} + \beta_{\text{mem}}(\text{Price Judgment}_{\text{mem}, jht}) + \beta_{\text{RF, mem}}(\text{Price Judgment}_{\text{RF, mem}, jht}) \)

We estimated these six utility equations (S.1, S.2, S.3, M.1, M.2, M.3) for each of the three product categories using mixed multinomial logit regression in Limdep NLOGIT 3. The parameter estimates, t-values, and weighting parameters for these 18 models appear in Table 1 (Equations S.2 and M.2) and the Web Appendix (Equations S.3, S.4, M.1, and M.3; see http://www.marketingpower.com/jmroct09). We estimated the weighting parameters \( \delta \) (Equation 2), \( \alpha \) (Equation 4), and \( \omega \) (Equations 8 and 9) using the procedures by Fader, Lattin, and Little (1992). The signs of the significant parameter estimates were consistent with prior literature and our expectations; that is, loyaltyjht, displayjht, and featurejht had positive signs, while pricejudgmentjht and pricejht had negative signs.

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5In the general case, in which the parameters are correlated, \( \Gamma \) is a lower triangular matrix. We include the K(K + 1)/2 parameters \( \gamma_{11}, \gamma_{12}, \gamma_{22}, \gamma_{13}, \gamma_{23}, …, \gamma_{1K}, \gamma_{2K}, …, \gamma_{KK} \) instead of the standard deviations \( \sigma \). We use these estimates to construct the estimated \( \Sigma \).

6We observed household \( h \) on \( T_h \) occasions. This panel aspect of the data is accommodated in the sampling process by drawing a single \( \beta \) per household and holding it (and the heterogeneity) constant across multiple occasions.

7Consistent with previous research (e.g., Briesch et al. 1997; Mazumdar and Papalia 2001), we include loss (L) and gain (G) parameters and exclude price in Models S.1 and S.3 to avoid the identification problem associated with Equation 3.
Table 1
RANGE–FREQUENCY MODEL PARAMETER ESTIMATES

<table>
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<th>Variables</th>
<th>S.2 Ketchup</th>
<th>S.2 Tuna</th>
<th>S.2 Stick Margarine</th>
<th>M.2 Ketchup</th>
<th>M.2 Tuna</th>
<th>M.2 Stick Margarine</th>
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<tr>
<td>PJRF, stim, jht</td>
</tr>
<tr>
<td>PJRF, mem, jht</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Estimated Standard Deviation of the Parameter Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>Featurejht</td>
</tr>
<tr>
<td>Displayjht</td>
</tr>
<tr>
<td>Loyaltyjht</td>
</tr>
<tr>
<td>Brand 1</td>
</tr>
<tr>
<td>Brand 2</td>
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<tr>
<td>Brand 3</td>
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<tr>
<td>Brand 4</td>
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<tr>
<td>Brand 5</td>
</tr>
<tr>
<td>Pricejht</td>
</tr>
<tr>
<td>PJRF, stim, jht</td>
</tr>
<tr>
<td>PJRF, mem, jht</td>
</tr>
</tbody>
</table>

Weights
δ | .660 | .705 | .716 | .660 | .705 | .716
w | .229 | .381 | .140 | .221 | .255 |

Notes: We provide the estimated mean (b) and standard deviation (s) of the parameter distribution for the utility models containing the range–frequency price judgment in the stimulus-based choice context (S.2) and in the memory-based choice context (M.2) across each product category. The corresponding parameter estimates for Equations S.1, S.3, M.1, and M.3 appear in the Web Appendix (http://www.marketingpower.com/jmroct09). The weights are the parameter estimates for δ in Equation 2 and w in Equations 8 (S.2) or 9 (M.2).

Hypotheses Tests
To test H1, we first considered the range–frequency parameter estimates and their elasticities. Next, we compared the fit of the three stimulus-based models and the fit of the three memory-based models. Because some utility models are not nested, we employed the estimation sample Bayesian information criteria (BIC; Schwartz 1978) and the validation sample log-likelihoods. Finally, we conducted a statistical test of the hypotheses using the likelihood ratio of the nested models (i.e., S.1 is nested within S.3, and M.1 is nested within M.3). All model log-likelihoods, BICs, and validation sample log-likelihoods appear in Table 2.8

Stimulus-based price judgments (H1a). As Table 1 shows, the range–frequency price judgment (PJRF, stim) had a significant, negative effect on choice for each product category (p < .05), and the standard deviation of the parameter distribution was significant for tuna and stick margarine (p < .05). Furthermore, we computed the elasticities for range–frequency price judgments in Equation S.2. We illustrate with direct elasticities for tuna.9 Across the four tuna brands, direct price judgment elasticities ranged from –.24 to –.56. These values are similar in magnitude to direct elasticities obtained in brand choice models reported in the literature (e.g., Jones 1997; Sun, Neslin, and Srinivasan 2003).

Next, we directly compared the fit of models S.1 (baseline price judgment), S.2 (range–frequency price judgment), and S.3 (both price judgments). As Table 2 shows,
Price Judgments and Range–Frequency Theory

Table 2
MODEL FIT STATISTICS: COMPARING BASELINE AND RANGE–FREQUENCY PRICE JUDGMENTS

<table>
<thead>
<tr>
<th>Model</th>
<th>Stimulus-Based Context</th>
<th>Memory-Based Context</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LL np BIC Val LL</td>
<td></td>
</tr>
<tr>
<td><strong>Ketchup</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S.1</td>
<td>-613.08 44 1524.92</td>
<td>-314.43</td>
</tr>
<tr>
<td>S.2</td>
<td>-608.54 44 1515.85</td>
<td>✓ -299.42   ✓</td>
</tr>
<tr>
<td>S.3</td>
<td>-603.66 44 1573.97</td>
<td>✓ -312.80   ✓</td>
</tr>
<tr>
<td><strong>Tuna</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S.1</td>
<td>-1551.24 44 3450.49</td>
<td>-1273.22</td>
</tr>
<tr>
<td>S.2</td>
<td>-1545.34 44 3438.68</td>
<td>✓ -1195.30   ✓</td>
</tr>
<tr>
<td>S.3</td>
<td>-1535.85 44 3498.75</td>
<td>-1199.04</td>
</tr>
<tr>
<td><strong>Stick Margarine</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S.1</td>
<td>-1418.79 65 3350.31</td>
<td>-1142.30</td>
</tr>
<tr>
<td>S.2</td>
<td>-1407.67 65 3328.05</td>
<td>✓ -1125.91   ✓</td>
</tr>
<tr>
<td>S.3</td>
<td>-1395.88 65 3399.13</td>
<td>✓ -1097.77   ✓</td>
</tr>
</tbody>
</table>

Notes: We provide the estimation sample log-likelihoods (LL), number of parameters estimated (np), estimation sample Bayesian information criteria (BIC), and validation sample log-likelihoods (Val LL) for three product categories. Models S and M indicate utility equations in the stimulus-based and memory-based choice context, respectively. Models 1, 2, and 3 indicate the baseline price judgment, the range–frequency price judgment, and both price judgments, respectively. The check marks indicate the models with the best BIC (in-sample fit) and validation log-likelihood (holdout sample fit) values in both the stimulus-based and memory-based contexts.

Memory-based price judgments (H1b). To determine the time horizon, \( \phi \), in Equation 9, we calculated the range–frequency price judgments using only the brand prices available to household \( h \) one month before purchase occasion \( t \), two months before \( t \), and so on, up to 12 months before purchase occasion \( t \). We then estimated Model M.2 for each time horizon and found that the highest log-likelihoods occurred at four, seven, and ten months back for margarine, ketchup, and tuna, respectively. Thus, we selected the time horizon associated with the highest log-likelihood in each product category to construct the range–frequency price judgments for the remaining analyses.

As Table 1 shows, the range–frequency price judgment (\( \text{PJ}_{\text{RF, mem}} \)) had a significant, negative effect on choice for each product category (\( p < .05 \)), and the standard deviation of the parameter distribution was significant for tuna and stick margarine (\( p < .05 \)). Across the four tuna brands, the direct elasticities for range–frequency price judgments in Model M.2 ranged from \(-.44 \) to \(-.73 \), which are similar in magnitude to the price elasticities reported in the literature (e.g., Jones 1997; Sun, Neslin, and Srinivasan 2003).

Next, we compared the fit of Models M.1 (baseline price judgment), M.2 (range–frequency price judgment), and M.3 (both price judgments). As Table 2 shows, the estimation sample BICs are lower for M.2 than for M.1 or M.3 across all product categories. Furthermore, the validation sample log-likelihoods are higher for Equation M.2 in the ketchup and tuna categories and for Equation M.3 in the stick margarine category. Thus, the range–frequency price judgments are supported by both the in-sample fits and the holdout samples.

To provide a statistical test for \( H_1b \), we used the likelihood ratio test to determine whether Model M.3 (both price judgments) had a significantly higher log-likelihood than Model M.1 (baseline price judgment). Across all product categories, the range–frequency price judgment provided a significant increase in the log-likelihood (ketchup: \( \chi^2 = 41.0, \text{d.f.} = 10, p < .001 \); tuna: \( \chi^2 = 33.6, \text{d.f.} = 10, p < .001 \); stick margarine: \( \chi^2 = 26.3, \text{d.f.} = 12, p = .006 \)). Thus, we find support for range–frequency price judgments within the domain of memory-based brand choice (\( H_{1b} \)).

Importance of range–frequency price judgments (\( H_2 \)). The influence of the range–frequency price judgment should increase with the variance (\( H_{2a} \)) and skew (\( H_{2b} \)) of the reference price distribution. To test \( H_{2a} \), we created a dummy variable in which \( \text{Var}_{\text{price}_{\text{het}}} \) is 0 if \( \text{price}_{\text{het}} = \text{price}_{\text{het}-1} = \ldots = \text{price}_{\text{het1}} = 1 \) and 1 otherwise. We then added \( \text{Var}_{\text{price}_{\text{het}}} \) and the interaction between \( \text{Var}_{\text{price}_{\text{het}}} \) and the range–frequency price judgment (Equation 9) to Equation M.2. As in our prior analysis, the range–frequency price judgment had a significant, negative effect on choice for each product category (\( p < .001 \)). In addition, and consistent with \( H_{2a} \), the interaction was negative and significant for each product category (\( p < .001 \)). Thus, the range–frequency price judgment had a stronger impact when the reference price distribution exhibited variance than when the distribution exhibited no variance.

We tested \( H_{2b} \) in a similar manner. Here, we computed the skewness of brand prices for each household up to purchase occasion \( t \). We then performed a median split on the absolute value of these measures and created a dummy variable in which \( \text{Skew}_{\text{het}} \) is 0 if the skewness measure was
below the median and 1 if it was above the median. We added Skew\_jht and the interaction between Skew\_jht and the range–frequency price judgment (Equation 9) to Equation M.2. Again, the range–frequency price judgment had a significant, negative effect on choice (p < .001), and the interaction was negative and significant for each product category (p < .05). Thus, the range–frequency price judgment had a stronger impact when the reference price distribution was more skewed than when the distribution was less skewed.

**Moderation of the weighting parameter (H3).** To test H3a, we created a dummy variable in which Trend\_jht is 1 if the slope of a regression between price\_jht and purchase occasion t differed significantly from zero at \( \alpha = .10 \) and 0 if otherwise. We then employed Equation M.2 and redefined w in Equation 9 as \( w = \alpha_1 + \alpha_2 \cdot \text{Trend}_jht \). Using the approach outlined in the Web Appendix (see http://www.marketingpower.com/jmroct09), we computed w and tested for the significance of \( \alpha_2 \). As we expected, \( \alpha_2 \) was negative and significant for each product category (ketchup: t = -1.93, p = .027; tuna: t = 2.00, p = .023; margarine: t = -3.07, p = .001). Thus, consistent with H3a, frequency received more weight (i.e., w was lower) when a household had been exposed to an increasing or decreasing trend of prices than when the household had not experienced a trend of prices (ketchup: w\_no trend = .385, w\_trend = .004; tuna: w\_no trend = .220, w\_trend = .053; margarine: w\_no trend = .442, w\_trend = .061).

To test H3b, we used the same approach as outlined previously. We created a dummy variable in which Coupuser\_jht was 1 if the household used a coupon on any purchase occasion and 0 if otherwise. As we expected, \( \alpha_2 \) was positive and significant for each product category (ketchup: t = 1.68, p = .047; tuna: t = 5.02, p < .001; margarine: t = 2.93, p = .002). Thus, consistent with H3b, range received more weight (i.e., w was higher) for households that used coupons than for households that did not use coupons (ketchup: w\_coupon = .361, w\_no coupon = .117; tuna: w\_coupon = .342, w\_no coupon = .008; margarine: w\_coupon = .297, w\_no coupon = .044).

**GENERAL DISCUSSION**

Brand choice models currently operationalize reference price as a single-point summary measure of the price distribution (Mazumdar, Raj, and Sinha 2005). Although these models capture central tendency effects, they are unable to account for the reference price distribution’s range, modality, and skew (Janiszewski and Lichtenstein 1999; Niedrich, Sharma, and Wedell 2001). To capture effects beyond the first moment of the reference price distribution, we formulated consumer price judgments using range–frequency theory (Parducci 1965).

We found that stimulus-based and memory-based range–frequency price judgments showed significant effects after accounting for the baseline price judgments. Moreover, the influence of range–frequency price judgments increased with the variance and skew of the reference price distribution. Finally, we found that the weighting parameter, which measures the relative importance of range versus frequency effects, was influenced by whether the consumer saw a trend of brand prices or was a coupon user. Consumers who saw a price trend were more attuned to frequency effects, whereas those who used coupons were more influenced by range effects. We conclude that actual choice behavior in retail environments is affected not only by the first moment but also by the entire reference price distribution.

We note the limitations that are common to research using scanner panel data. In particular, sampling issues may reduce the representativeness of the panel and the generalizability of the results. However, the ranges of market shares captured by the target brands for the product categories examined here (68%–87%) are consistent with published reference price research. In addition, researchers have shown that despite the sampling problems, results based on scanner panel data are reasonably accurate (e.g., Gupta et al. 1996; Silva-Risso, Bucklin, and Morrison 1999).

**Implications for Choice Modeling**

In the stimulus-based choice context, range–frequency price judgments led to superior model fits in all product categories. Thus, in general, we recommend the use of range–frequency price judgments over single-point measures (e.g., Hardie, Johnson, and Fader 1993). However, our approach does not account for loss aversion. Although it is straightforward to use a single-point reference price measure, losses and gains are not so clearly identified when a price judgment is based on the location of the focal price within a distribution of prices. Accounting for loss aversion using range–frequency theory is a worthwhile avenue for further research.

In the memory-based choice context, range–frequency price judgments also led to superior model fits in all product categories. However, it is important to note that range–frequency theory and the exponentially weighted model are complementary theories. Whereas range–frequency theory is well suited to capture distributional effects but not temporal effects, the reverse is true for the exponentially weighted model. Thus, in general, we recommend employing both approaches and note that including range–frequency price judgments is imperative when reference prices are not well characterized by the first moment.

**Implications for Pricing Theory**

Winer (1999, p. 349) argues that “it is incumbent on us to be concerned about the generalizability of research results beyond the lab into other contexts” and further notes that “scanner data studies that support results found in the lab provide strong supporting evidence of external validity.” Because range–frequency theory has not been previously tested outside the laboratory in any reference price context, an important contribution of this research is that it provides evidence of external validity. Our findings extend previous research on price judgments of student participants in the laboratory (Janiszewski and Lichtenstein 1999; Niedrich, Sharma, and Wedell 2001) to the domain of actual brand choices of households as recorded in scanner panel data.

This research suggests an alternative paradigm for the representation of reference prices. The traditional view of reference price is based on prototype theory, in which all relevant price information is integrated into a single prototypical value (Mazumdar, Raj, and Sinha 2005). A price
judgment is the difference between a focal price and the category prototype (e.g., Helson 1964). Classification decisions are based on the similarity of new prices to the prototypes of alternative categories; the selected category prototype is integrated with the new price using an anchoring and adjustment process. In contrast, our findings are more congenial with exemplar theory, which assumes that category knowledge is episodic and represented by the individual prices themselves (Nosofsky and Zaki 2002). A price judgment is based on the location of the focal price within the set of prices activated in memory or available in the environment. Classification decisions are then based on the similarity of new prices to the exemplars of alternative categories, and the selected category is updated to include the new price.

Consistent with the accessibility–diagnosticity model (Feldman and Lynch 1988), the exemplar conceptualization highlights the impact of consumer retrieval processes and the potential effects of differential weighting. In prototype theory, reference price activation is all or none. In contrast, exemplar theory suggests that the activation and weighting of reference prices is a complex and dynamic process that can be altered over purchase occasions. In support of this notion, we found that consumers exposed to a trend of prices over time exhibited higher frequency effects and that coupon users had higher range effects. Because price judgments depend on the evoked set, factors that affect the retrieval and weighting of price exemplars represent a worthwhile area for further research.

Implications for Pricing Strategy

Because of the prevalence of high–low pricing, the distribution of brand prices for consumer goods is often negatively skewed (Rao, Arjunji, and Murthi 1995), suggesting that a brand is more frequently at full price than at the discounted price (e.g., 65% high, 35% low). This marketplace observation motivates the question, Is the negatively skewed distribution found in practice an optimal pricing strategy? In contrast to baseline models, range–frequency theory predicts that the answer is no. The explanation for this prediction is that in a negatively skewed price distribution, the prices that anchor the range are lower than those in a positively-skewed price distribution with the same mean. Thus, range–frequency theory suggests that managers should consider a positively skewed distribution by raising the full price of their brands somewhat and employing smaller but more frequent discounts (e.g., 35% high, 65% low), such that the overall mean price remains the same.

Another common concern for managers is the negative long-term impact of price promotions, in which deep discounts can reduce reference prices, and thus normal prices may appear less attractive in the future (e.g., Kalwani and Yim 1992). Although our data suggest that the reference prices consumers use in constructing price judgments appear limited to a several-month period, we also found that the range effect, which should be strongly affected by deep discounts, increased with coupon usage and decreased with a trend of brand prices. Thus, additional research on moderators of the weighting factor, w, in range–frequency theory (e.g., characteristics of the product, choice environ-

REFERENCES


Lichtenstein, Donald R., Richard G. Netemeyer, and Scot Burton (1991), “Using a Theoretical Perspective to Examine the Psychological Construct of Coupon Proneness,” in Advances in


