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MODELING LOSS AVERSION AND REFERENCE DEPENDENCE EFFECTS ON BRAND CHOICE

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Based upon a recently developed multiattribute generalization of prospect theory's value function (Tversky and Kahneman 1991), we argue that consumer choice is influenced by the position of brands relative to multiattribute reference points, and that consumers weigh losses from a reference point more than equivalent sized gains (loss aversion). We sketch implications of this model for understanding brand choice.

We develop a multinomial logit formulation of a reference-dependent choice model, calibrating it using scanner data. In addition to providing better fit in both estimation and forecast periods than a standard multinomial logit model, the model's coefficients demonstrate significant loss aversion, as hypothesized.

We also discuss the implications of a reference-dependent view of consumer choice for modeling brand choice, demonstrate that loss aversion can account for asymmetric responses to changes in product characteristics, and examine other implications for competitive strategy.

(Brand Choice; Buyer Behavior; Choice Models; Reference Effects)

1. Introduction

Consider the following scenarios:

- You and a friend go to your favorite Chinese restaurant after a long hiatus. You remember the restaurant for its delicate and complex dumplings and fiery hot dishes. Although expensive by Asian restaurant standards, you think it is a very good value. You are anxious to see your friend's reaction because, although he has never visited this restaurant, his tastes in Asian food are almost identical to yours. You are surprised to learn that the restaurant has a new menu with entrees cheaper than before, but with some decrease in quality. When comparing your reactions to the meal, you are startled to find that, while you were disappointed, your friend was delighted to find such a reasonably priced, yet high quality restaurant.
- You reach into your refrigerator one morning and notice that your customary brand of orange juice is missing. Your spouse explains that it was out of stock and that he bought a more expensive, higher quality brand. In this situation, is your evaluation of the new brand independent of your favorite brand? Do you savor the increased quality? Worry about the increased price? If instead you faced a lower quality, lower cost brand, how would you feel about the savings? The decreased quality? And would you have the same intensity of feelings about an increase versus a decrease in quality, even if they are of the same magnitude?

These examples illustrate the notion that consumers often evaluate product attributes relative to some reference level, and not simply in terms of absolute attribute levels. In contrast, the standard economic analysis of consumer choice assumes that, aside from wealth effects, preferences are invariant of current asset position (or similar “reference points”). Moreover, these examples also suggest that changes from these reference points may be valued differently depending whether they are gains or losses relative to some reference point. One intuition, supported by significant empirical evidence, suggests that losses will be weighted more heavily than the equivalent sized gains, a property known as loss aversion (Tversky and Kahneman 1991).

The goal of this paper is to further explore two related concepts: (1) that brand choice is influenced by the position of brands relative to multiattribute reference points, and (2) that consumers weigh losses from a reference point more than equivalent-sized gains (loss aversion). We employ recent work describing reference-dependent choice with multiattribute alternatives (Tversky and Kahneman 1991), and apply it to the analysis of brand choice. To assess its descriptive validity, we develop and estimate a multinomial logit model that incorporates reference dependence and loss aversion, and compare this model to more traditional models of brand choice. We close by discussing the implications of these concepts for models of consumer choice and brand competition.

2. Reference Dependence and Loss Aversion

Recently, a number of marketing scientists have developed models of brand choice which incorporate concepts from the behavioral pricing literature (Winer 1988). The bulk of these applications have examined reference prices and their effects on buyer behavior and brand choice. Kalwani et al. (1990), Lattin and Bucklin (1989), and Winer (1986) use household-level models of brand choice calibrated using scanner panel data, while Raman and Bass (1988) use aggregate market share data. Putler (1992) develops a theoretical economic model of consumer choice that embodies reference price effects. Some researchers have investigated reference effects for consumer promotions, e.g., Lattin and Bucklin (1989) using scanner data, and Kalwani and Yim (1992) in an experimental study.

A number of these modeling efforts investigate whether there is any asymmetry in consumer response to deviations of actual prices from reference prices. This asymmetric effect is typically motivated, at least in part, by the well-known value function of *prospect theory* (Kahneman and Tversky 1979). However, these applications face an important barrier: prospect theory was originally developed to describe choice among simple risky prospects, that is, probabilistic outcomes described by a single attribute (often amounts of money) and few outcomes (see, for example, Currim and Sarin’s 1989 model-based empirical test of prospect theory’s propositions). Thus most applications to brand choice have involved a single attribute, usually price.

More recently, Tversky and Kahneman (1991) develop a theoretical framework for value functions involving multiple attributes. This has broad implications for the analysis of consumer choice. The basic ideas are that: (1) each choice alternative can be decomposed into a set of values on attributes, (2) each attribute can be described by its own value function, with its own specific characteristics, and (3) alternatives are evaluated relative to a reference point.

Note that in most of the reference price models discussed above, each choice alternative has *its own reference price* against which the actual price for that choice alternative is compared. Although there is a segment of the population that appears to be quite knowledgeable about prices and promotional activity (Krishna, Currim, and Shoemaker 1991), most consumers have surprisingly poor memory for prices (Dickson and Sawyer 1990). We must, therefore, question the idea that consumers have distinct (and accurate) ref-

erence prices for each choice alternative formed on the basis of exposure to past prices and promotional activity. Tversky and Kahneman’s new framework suggests that all choice alternatives are compared against a *common* reference point in the multiattribute space. In other words, for any given attribute (e.g., price), the attribute level for each choice alternative is compared to the *same* reference level (as opposed to alternative-specific reference levels in the reference price models). It must be remembered that this reference-dependent evaluation of an attribute applies not just to price (as is the case for reference price models) but to all other product attributes (e.g., quality) as well.

As in the single-attribute case (Kahneman and Tversky 1979), there are three characteristics of the value function:

- Reference dependence: The carrier of an attribute’s value is not based on its absolute level but rather on its deviation from some reference level (which results in a “gain” or “loss”).
- Loss aversion: The value function is steeper for losses than for gains. In other words, a loss decreases value more than an equivalent sized gain will increase value.
- Diminishing sensitivity: The marginal value of both gains and losses decreases with their size; the first sip of beer tastes the best, and the first dollar lost hurts the most.

To illustrate briefly these properties and their implications, consider the orange juice example at the beginning of the paper. Figure 1 portrays a two-attribute product space (price and quality), with price labeled so that a lower price is better. We consider three different reference points, p , q and r , all equivalent on quality but differing on price. In this product space, we introduce two brands, x and y , both members of some efficient set (i.e., neither dominates the other). We further assume that when evaluated from reference point q , a consumer is indifferent between x and y , which, after Tversky and Kahneman (1991), we denote as $x \approx_q y$. This is read as “ x and y are indifferent when evaluated from reference point q .”

Loss aversion implies that indifference curves are steeper when they represent losses relative to the reference point. Therefore, if a consumer is indifferent to the two brands from reference point q , that consumer will prefer x if the brands are evaluated from reference point r , i.e., $x >_r y$. To see this, note that from q , none of the product attributes represents a loss: y is equivalent in price, and much better in quality, while x is superior in both quality and price. The indifference relationship $x \approx_q y$ suggests that the advantage, relative to q , that y has in quality matches the two smaller advantages possessed by x . However, when viewed from r , y now has a disadvantage (loss) on price, and x loses its price advantage. Notice that the shift in reference points deletes the x price advantage

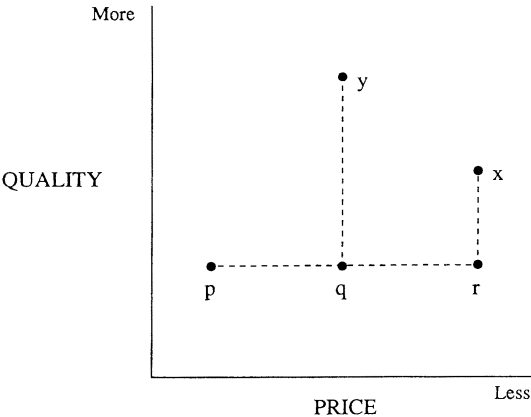


FIGURE 1. Illustration of Loss Aversion and Diminishing Sensitivity

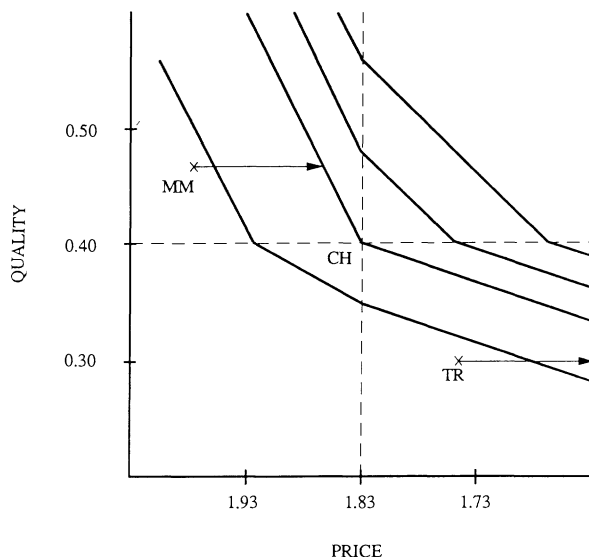


FIGURE 2. Illustration of Asymmetric Response

and creates a price disadvantage for y of the same magnitude, but with opposite sign. Loss aversion implies that the new disadvantage of y introduced by the shift from q to r , must outweigh the forfeiture of x 's price advantage.

Diminishing sensitivity can be represented in Figure 1 by comparing preferences from reference points p and q . As before, assume that a consumer is indifferent between x and y from q : $x \approx_q y$. Diminishing sensitivity implies that from reference point p , $y >_p x$ ("y will be preferred to x from reference point p ") because while the differences in quality (dimension 2) remain unchanged, we have added a constant amount to the advantages that both brands had on price, dimension 1. Diminishing sensitivity suggests that the difference between the brands on price is seen as smaller than before. Since the difference in quality remains unchanged, y will now be preferred.¹

With additional assumptions it is possible to specify further the preference orders that emerge from a reference-dependent value function. (See Tversky and Kahneman 1991 for further details.) First, a reference structure is said to be *decomposable* if (1) there exist increasing functions that map the values of each dimension into the reals, and (2) these functions of the attributes can be combined by an increasing function to produce an overall value for the brands. In other words, decomposability implies that the effect of a reference point can be captured by a separate monotonic function on each attribute, and that attributes can be combined by another monotonic function. One example would be an additive function in which the utility of an option, x , defined by two attributes, x_1 and x_2 , evaluated from a reference point r , is given by U_r , such that $U_r(x_1, x_2) = R_1(x_1) + R_2(x_2)$. The functions R_1 and R_2 are called the reference functions associated with a two-attribute reference point r .

For an additive reference structure, Tversky and Kahneman describe a property termed *constant loss aversion*² which describes the degree of loss aversion for each attribute, given by:

¹ In the analysis that follows, we model the effects of reference dependence and loss aversion, but assume constant sensitivity. A further discussion of diminishing sensitivity and its implications can be found in Tversky and Kahneman (1991, pp. 1048–1050).

² Formally, a reference structure (X, \succeq_r) fulfills constant loss aversion if the attribute utilities, u_i , can be represented by a mapping into the real numbers ($u_i: X_i \rightarrow \text{Reals}$), and constants $\lambda_i > 1$, $i = 1, 2, \dots$ such that (i) decomposability holds, and (ii) Equation (1) holds for all x and r in X .

$$R_i(x_i) = \begin{cases} u_i(x_i) - u_i(r_i), & \text{if } x_i \geq r_i, \\ \lambda_i[u_i(x_i) - u_i(r_i)], & \text{if } x_i < r_i. \end{cases} \quad (1)$$

Thus, for reference structures that satisfy constant loss aversion, changes in the preference order induced by a shift of reference point can be described in terms of two constants, λ_1 and λ_2 , which are interpreted as the coefficients of loss aversion for dimensions 1 and 2, respectively. This is illustrated by the set of indifference curves in Figure 2 (see §4) which are associated with an additive, decomposable reference structure and linear $u_i(\cdot)$. The two-attribute product space is divided into four quadrants by the reference point. In the top right quadrant the usual analysis applies, and the slope of the indifference curves represents the tradeoffs between the two attributes. In the other quadrants, the indifference curves reflect the impact of loss aversion on one or more attributes. For example, the lower right quadrant is characterized by loss aversion for quality, so small changes on the quality (vertical) dimension correspond to relatively large changes in value.

3. Modeling Reference Dependence and Loss Aversion

A significant challenge presented in modeling reference dependence and loss aversion is the identification of the reference point for each consumer. In experimental studies, reference points can be manipulated by changing the status quo or by varying a target or norm. In correlational applications such as ours, identifying reference points is more difficult.

One of many possibilities is to assume that brands themselves serve as reference points, and that the reference brand is the most recent brand purchased by each household. We believe this is a sensible choice for several reasons. First, after Samuelson and Zeckhauser (1988), we argue that the currently held alternative serves as the status quo and thus offers a natural candidate for comparison. Any other brand is encoded as a change (potentially both gains and losses) from this brand. Behaviorally, it seems likely that characteristics of the brand last purchased will be more available in memory and will, in most cases (particularly with perishables), correspond with the most recent consumption experience. Ultimately the success of last brand purchased will be assessed by empirical tests of alternative formulations of reference brand.

If reference dependence and loss aversion affect consumer choice, we can test four important empirically testable propositions. First, a model including reference points for all attributes and allowing separate tradeoffs for losses and gains should provide a better fit. Second, the coefficients for each product attribute should differ for gains and losses relative to a reference point, with the absolute value of the coefficient for losses being larger than the coefficient for gains in each case. Third, the household-specific reference brands used in this model will capture a significant amount of the cross-sectional heterogeneity seen in traditional brand choice models. Therefore measures of heterogeneity should be substantially smaller for the reference-dependent model. Finally, if the reference point varies over time, the model will also be capturing a source of preference nonstationarity, and therefore we expect measures of nonstationarity to decrease in a reference-dependent model.

We first discuss the overall structure of the proposed model using a two-attribute case, price and quality. We then cover the specific definition and measurement of each of the model's components. After offering more details on the propositions mentioned above, we discuss the estimation results for three competing models.

3.1. Model Specification

We use the familiar multinomial logit (MNL) model (Guadagni and Little 1983, McFadden 1974), which models choice probabilities using the following structure:

$$\text{MNL}_{hjt} = \frac{e^{v_{hjt}}}{\sum_k e^{v_{hkt}}}, \quad \text{where}$$

MNL_{hjt} = the MNL probability that household h chooses brand j on purchase occasion t ,

$v_{hjt} = \sum_m \beta_m x_{hjtm}$ = the deterministic component of utility of brand j for household h on purchase occasion t ,

x_{hjtm} = the m th explanatory variable for brand j and household h on purchase occasion t , and

β_m = estimated logit coefficient.

Like many contemporary MNL models, we include information on promotions and prices for each brand, as well as a loyalty measure to capture cross-sectional and time-varying heterogeneity in the choice process. However, in a departure from most scanner-data based MNL applications, we also introduce a measure of quality for each brand. With this set of explanatory variables the typical specification for the deterministic component of utility would be:³

$$v_{hjt} = \beta_1 \text{QUALITY}_{hjt} + \beta_2 \text{PRICE}_{hjt} + \beta_3 \text{FEATURE}_{hjt} + \beta_4 \text{LOYALTY}_{hjt}. \quad (2)$$

We discuss the measurement of these variables in §3.4.

Since this model does not distinguish between gains and losses, nor incorporates reference effects, it implicitly assumes “loss neutrality” for both attributes (i.e., the loss aversion coefficients for price, λ_p , and quality, λ_q , both equal 1). More generally, we posit that choice alternatives are evaluated with respect to a reference brand and that loss aversion exists.

To specify a logit model that includes reference dependence and loss aversion, we replace the $\beta_1 \text{QUALITY}_{hjt}$ and $\beta_2 \text{PRICE}_{hjt}$ terms in (2) with reference functions of the form given in (1). In particular, we assume an additive, decomposable reference structure, constant loss aversion, and constant sensitivity (i.e., $u_i(x_i) = \beta_i x_i$). Therefore, if brand r is the reference brand for household h at purchase occasion t , the deterministic component of utility for brand j becomes:

$$\begin{aligned} v_{hjrt} = & \beta_1 [\text{QUALGAIN}_{hjrt} + \lambda_q \text{QUALLOSS}_{hjrt}] \\ & + \beta_2 [\text{PRICEGAIN}_{hjrt} + \lambda_p \text{PRICELOSS}_{hjrt}] \\ & + \beta_3 \text{FEATURE}_{hjt} + \beta_4 \text{LOYALTY}_{hjt}, \quad \text{where} \end{aligned} \quad (3)$$

QUALGAIN_{hjrt} = the amount by which the quality of brand j exceeds that of the reference brand r for household h at purchase occasion t ,

QUALLOSS_{hjrt} = the amount by which the quality of brand j is below that of the reference brand r ,

PRICEGAIN_{hjrt} = the amount by which the price of brand j is below that of the reference brand r , and

PRICELOSS_{hjrt} = the amount by which the price of brand j exceeds that of the reference brand r ,

For the quality attribute, a “gain” for brand j occurs when its level is above the reference brand’s quality level, and a “loss” occurs when brand j ’s quality is below the reference brand’s. For price, the same logic applies, but with a change of sign, since increases in price are considered losses.

Let Q_j be the quality of brand j (constant over time and across consumers), and P_{hjt} the price of brand j observed by consumer h on purchase occasion t . Let r be the brand

³ Note that it is the nature of the product quality measure (i.e., homogeneous across households and stationary), not the model structure, that precludes the use of brand-specific constants in the models discussed here. However, our loyalty measure includes a set of brand-specific parameters which can capture these same effects.

index of the reference brand on the purchase occasion under consideration. The gain and loss terms are calculated as follows:

If the quality of brand j equals or exceeds that of the consumer's reference brand (i.e., $Q_j \geq Q_r$),

$$\text{QUALGAIN}_{hjt} = Q_j - Q_r, \quad \text{QUALLOSS}_{hjt} = 0.$$

If brand j is lower in quality than the reference brand (i.e., $Q_j < Q_r$),

$$\text{QUALGAIN}_{hjt} = 0, \quad \text{QUALLOSS}_{hjt} = Q_j - Q_r.$$

If the price of brand j equals or is lower than that of the reference brand (i.e., $P_{hjt} \leq P_{hrt}$),

$$\text{PRICEGAIN}_{hjt} = P_{hrt} - P_{hjt}, \quad \text{PRICELOSS}_{hjt} = 0.$$

If brand j is more expensive than the reference brand (i.e., $P_{hjt} > P_{hrt}$),

$$\text{PRICEGAIN}_{hjt} = 0, \quad \text{PRICELOSS}_{hjt} = P_{hrt} - P_{hjt}.$$

3.2. A Temporal Reference Price Model

Note that these variable definitions differ from prior work in several ways. Unlike previous work employing reference price terms, we look at the difference between the prices of the brand under consideration and the reference brand *at the time of purchase*. There is no temporal reference price calculated for each brand as a function of purchases, historical prices, or promotional activity (e.g., Kalwani et al. 1990, Lattin and Bucklin 1989, Winer 1986) or directly elicited from subjects in an experiment (Kalwani and Yim 1992). A more important difference, however, is that this model simultaneously estimates the effects of loss aversion on two (and potentially more) attributes, not just price. As a result, it allows us to study the relative loss aversion across attributes.

For comparison, we operationalize a temporal reference price model similar to those used in prior research. We define temporal reference price as an exponentially smoothed average of past observed prices for each brand:

$$\text{RPRICE}_{hj(t+1)} = \gamma \text{RPRICE}_{hjt} + (1 - \gamma)P_{hjt}. \quad (4)$$

Price gains and losses are generated by differences between this smoothed reference price and the actual observed price at each purchase occasion:

If the price of brand j is at or below its current reference price (i.e., $P_{hjt} \leq \text{RPRICE}_{hjt}$),

$$\text{PRICEGAIN}_{hjt} = \text{RPRICE}_{hjt} - P_{hjt}, \quad \text{PRICELOSS}_{hjt} = 0.$$

If the price of brand j is above its current reference price (i.e., $P_{hjt} > \text{RPRICE}_{hjt}$),

$$\text{PRICEGAIN}_{hjt} = 0, \quad \text{PRICELOSS}_{hjt} = \text{RPRICE}_{hjt} - P_{hjt}.$$

Quality is included strictly as an absolute measure, and we also include the reference price variable by itself (Winer 1986). The deterministic component of utility for the temporal reference price model is as follows:

$$v_{hjt} = \beta_1 \text{QUALITY}_{hjt} + \beta_2 [\text{PRICEGAIN}_{hjt} + \lambda_p \text{PRICELOSS}_{hjt}] \\ + \beta_3 \text{RPRICE}_{hjt} + \beta_4 \text{FEATURE}_{hjt} + \beta_5 \text{LOYALTY}_{hjt}. \quad (5)$$

Note that this model requires one more parameter than the model shown in (3). While it does not use a loss aversion parameter for quality (λ_q), it has an extra logit coefficient (for RPRICE) and an exponential smoothing constant (γ) needed to obtain the reference prices.

3.3. Data

We use Information Resources, Inc., scanner panel data for refrigerated orange juice purchases in Marion, IN, to calibrate the model. The data set describes purchases over a 130-week period (January 1983 to July 1985) for a set of 200 randomly chosen households that made at least one category purchase in 1984. Over 80% of the orange juice purchases made by these households are from one of the six following brands (all in the 64-ounce size): Citrus Hill, Minute Maid, Tropicana Regular, Tropicana Premium, a regional brand, and a store brand. The model calibration period covers 1984, including 1,589 purchases. We employ the 1,490 purchases from 1983 for initialization purposes, and reserve 666 purchases from the first half of 1985 to use as a forecast period.

3.4. Definition of Measures

Quality. Scanner datasets do not provide any information about the perceived quality of each brand. It is generally not possible to directly assess panelists' quality perceptions of individual brands. As a result, we have to use non-panel-based measures of quality. As in other studies that have used quality variables (e.g., Gerstner 1985, Montgomery and Wernerfelt 1992), we utilize *Consumer Reports* quality ratings. We use a "sensory index" based on "judgments made by CU's trained panel of the freshness and intensity of each product's orange flavor" (*Consumer Reports* 1987, p. 78).

Objective ratings of quality, such as those provided by *Consumer Reports*, are imperfect measures of perceived product quality (see Hjorth-Andersen (1984) for a discussion of these issues). However, several factors recommend their use here. First, at the time these data were gathered, the refrigerated orange juice market was not very differentiated. The major partitioning of the category, represented by the introduction of "pulpy" and calcium-added varieties, occurred afterwards. Second, product quality is quite stable: subsequent *Consumer Reports* ratings show identical rank orders for the brands used here. Third, judgments of quality are relatively consensual and easily made. In fact, different quality labels appear in some brand names: Tropicana Regular vs. Tropicana Premium. Some of these quality differences result from objective factors, such as the production method (packaged fresh versus reconstituted from concentrate). Thus, while there is certainly more heterogeneity among individuals than acknowledged in our measure, there are substantive reasons why this quality measure should be appropriate.

The sample of brands tested by the Consumers Union included the four national brands in our data set but not the specific regional and store brands used in our study. Consequently, we infer quality ratings for these two brands by averaging the ratings of private label brands for three major regional chains to arrive at a proxy rating for the regional brand, while the proxy rating for the store brand is the average rating of three smaller store brands. The quality ratings are given in Table 1, along with the average prices for each brand over the calibration period.

TABLE 1
Quality and Average Prices

	Quality	Average Price
Citrus Hill	0.395	\$1.83
Minute Maid	0.474	1.98
Regional brand	0.254	1.76
Tropicana Regular	0.303	1.75
Store brand	0.114	1.33
Tropicana Premium	0.487	2.26

Price. We combine regular (depromoted) price and short-term price cuts into a single measure of “actual price paid,” i.e., net retail price (regular price, less any applicable price cuts).

Feature. This variable is a dichotomous (0/1) measure indicating the presence of any advertising in the local newspaper. It is a sporadic signal that rarely applies to more than one brand at a time, and is often processed by the consumer before entering the supermarket. These conditions suggest that consumers might not generally use feature information in a reference-dependent manner; as such, we do not model reference brand effects for features and instead include this measure as an ordinary logit variable.⁴

Loyalty. An important component in all household-level choice models is a measure of *brand loyalty*, or more precisely, cross-sectional and time-varying heterogeneity in brand preferences. Many researchers (e.g., Chintagunta et al. 1991; Jones and Landwehr 1988) have discussed the reasons for such variables and have offered different techniques to accomplish this task.

The most prominent loyalty measure, from Guadagni and Little (1983), uses an exponential smoothing approach to weight the past purchase history for each household:

$$\text{LOY}_{hj}(t+1) = \gamma \text{LOY}_{hj}(t) + (1-\gamma)y_{hjt}, \quad \text{where} \quad (6)$$

$\text{LOY}_{hj}(t)$ = loyalty of household h to brand j on purchase t ,

$y_{hjt} = 1$ if household h buys brand j on purchase occasion t , 0 otherwise, and

γ = smoothing parameter, $0 \leq \gamma \leq 1$.

Although many applications (e.g., Kalwani et al. 1990) have shown that this measure can capture cross-sectional and longitudinal differences quite well, it does not offer any summary statistics to convey the overall level of nonstationarity or cross-sectional heterogeneity. The γ parameter confounds both of these effects without offering any way to disentangle them. This shortcoming is particularly important in our case since we have specific hypotheses about how these constructs will change across model specifications.

Fader and Lattin (1993) present an alternative loyalty measure that not only performs as well as the exponentially smoothed measure but also provides clear estimates of cross-sectional heterogeneity and nonstationarity. This measure represents a generalized form of the beta-binomial-geometric model of Sabavala and Morrison (1981); we refer to it as the NSDM (nonstationary Dirichlet-multinomial) loyalty variable, and describe it in more detail in Appendix 1.

For a market with J brands, NSDM generates $J+1$ new parameters. The first J parameters, denoted as α_j , are brand-specific parameters that disclose the relative preference for each brand. Among the various benefits of these parameters is an indication of the overall level of preference heterogeneity. The *polarization index*, defined as $\phi = 1/(1 + \sum_j \alpha_j)$ (Jeuland et al. 1980, Sabavala and Morrison 1977), is a commonly used summary statistic for heterogeneity. It is bounded between 0 and 1: lower values indicate smaller differences across consumers (i.e., greater homogeneity) while values closer to 1 signify high levels of cross-sectional preference heterogeneity. Fader (1993) discusses others relevant properties and benefits of the α_j parameters.

The other NSDM parameter indicates the extent of nonstationarity in preferences across the dataset. This parameter (ν) can be interpreted as “the probability that the brand preferences for a certain household remain unchanged at a particular purchase

⁴ Some researchers (Kalwani and Yim 1992, Lattin and Bucklin 1989) have investigated the role of promotional expectations in brand choice. The results of recent work on consumer perception of promotional activity (Krishna 1991; Krishna, Currim, and Shoemaker 1991) suggest that for our dataset, in which promotional activity is infrequent with no apparent pattern, consumers have low expectations—if any—of a promotion during any given week. Consequently we see no need to incorporate such effects in our model specification.

occasion." In other words, if ν is near 1.0, then brand preferences tend to be very stable over time, but a value of ν closer to zero indicates a high degree of nonstationarity.

The results and discussion in Fader and Lattin (1993) suggest that this NSDM loyalty variable compares favorably with other methods for capturing cross-sectional and time-varying preference heterogeneity. The useful diagnostics that it generates make it a natural choice for the present analysis.

Reference Brand. Consistent with our earlier theoretical discussion, we operationalize reference points as the last brand purchased.⁵ In Appendix 2, we present summary results for five different reference-brand-generating schemes (including last brand purchased, which appears to be the best of the five). Pragmatically, last brand purchased is a very parsimonious definition. While more complex forms can be estimated, they involve assumptions about the characteristics of recall of prior decisions, product characteristics, etc., thereby bringing additional measurement and specification errors into the model. Nevertheless, we encourage future research into more complex, theoretically justified, reference-brand-generating procedures.

3.5. Model Predictions

In the next section we compare the reference-brand-dependent (RBD) model (Equation (3)) to two benchmark logit models: the standard model with no reference effects (Equation (2); denoted as NOREF), and the temporal reference price model (Equation (5); denoted as TEMPREF). We contrast these three models in terms of overall model fit and interpretations of the estimated parameters. Several comparisons deserve particularly close attention. Based on the earlier discussion, we offer predictions on four relevant issues: model fit, degree of loss aversion, and estimates of heterogeneity and nonstationarity. We discuss each in turn.

Model Fit. If reference dependence exists in consumer markets, the standard logit and temporal reference price models will miss potentially important sources of variance. If our specification captures both reference dependence and loss aversion, we should expect the RBD model to fit the observed choice data substantially better than the NOREF and TEMPREF models. Because the TEMPREF model is not a nested version of RBD, we use a non-nested test, from Ben-Akiva and Lerman (1985) to compare model fit. We also expect the RBD model to show stronger model fitting ability in the holdout forecast period.

Degree of Loss Aversion. The λ_p and λ_q coefficients in equation (3) convey the degree of loss aversion under the RBD model. A value of λ_p or λ_q above 1 indicates the presence of loss aversion for that attribute, and higher values of λ imply greater loss aversion. Thus we expect $\lambda_p > 1$ and $\lambda_q > 1$. While we cannot say with assurance whether consumers are more, or less, loss averse on price than on quality (i.e., whether λ_p is greater than, or less than, λ_q), Tversky and Kahneman (1991) suggest that ordinary monetary transactions may be seen as less of a loss than changes on other attributes. We therefore expect consumers to exhibit stronger loss aversion for quality compared to price, i.e., $\lambda_q > \lambda_p > 1$.

Estimates of Heterogeneity. The RBD theory suggests that a significant factor behind cross-sectional differences in brand choice will be differences in reference brands across households; this distinction is ignored in standard logit models. The use of household-level reference brands will eliminate some of the cross-sectional preference heterogeneity

⁵ There are several occasions for which the last brand purchased is unavailable (e.g., if a consumer bought a store brand last time but is now shopping in a different store). For these purchase occasions, we define the reference brand to be the available brand with the highest NSDM loyalty for that household at that time.

that is usually captured by the loyalty measure alone. Thus, we expect to see more homogeneous brand preferences (lower value of ϕ) for the RBD model compared to the NOREF and TEMPREF models.

Estimates of Nonstationarity. If the consumer choice process is reference dependent, changes in the reference brand over time will increase the *apparent* level of nonstationarity in preferences. Any model specification that fails to recognize reference dependence will therefore overstate the nonstationarity, confounding true nonstationarity in preferences with that due to changing reference points. We therefore expect to see less nonstationarity in consumer choice behavior (a higher value of ν) for the RBD model compared to the NOREF and TEMPREF models.

3.6. Model Estimation and Results

Because the NSDM loyalty measure involves a set of nonlinear parameters (ν and α_j 's), the full model can not be estimated directly with ordinary MNL algorithms. However, Fader et al. (1992) describe a simple iterative technique that allows for the simultaneous estimation of ordinary MNL coefficients and imbedded nonlinear parameters such as ν and the α_j 's. A few iterations of a standard MNL model will yield exact maximum likelihood estimates of the desired nonlinear parameters, along with estimates of their standard errors. The reader is referred to Fader et al. (1992) for a general description of the procedure.

Using this estimation procedure, we obtain parameter estimates for the three models described above. As an additional benchmark, we estimate a more typical logit model using the exponentially smoothed loyalty measure shown in equation (6) and no quality variable. We refer to this as the G&L (Guadagni and Little) model. Estimation results are shown in Table 2.

The RBD model, with its unconstrained loss aversion parameters, is notably stronger than all three alternative models. The non-nested model test statistic yields highly significant differences ($p < 0.001$) for all comparisons involving the RBD model. The NOREF and TEMPREF models are statistically indistinguishable, but both are significantly ($p < 0.001$) stronger than the G&L model. Differences in fit for the forecast period are less distinct, although all three models that employ the NSDM loyalty measure are considerably stronger than G&L.⁶

The estimated coefficients are generally significant and intuitively sound. Both loss aversion coefficients are significantly greater than 1, and as predicted, consumers tend to be considerably more loss averse for quality than for price.

The other two predictions are also supported: the RBD model indicates much lower levels of cross-sectional and longitudinal heterogeneity in preferences than the other models. Despite the RBD model's very low estimate of nonstationarity ($\nu = 0.954$) we can still reject the hypothesis that preferences are completely stationary.

To examine the incremental value of the various different reference effects embodied by the TEMPREF and RBD models, we ran several "hybrid" models incorporating different elements of each model. We found that excluding either of the RBD effects still leads to a sizeable improvement over the competing models ($LL = -1408$ for RBD quality alone, $LL = -1407$ for RBD price alone). Furthermore, adding the temporal reference price variable adds little to the full RBD model ($LL = -1403$). In summary, the RBD effects hold up very well individually or together, and seem to be quite robust to different model specifications.

⁶ If the G&L exponentially smoothed loyalty measure is used in place of the NSDM measure for the NOREF, TEMPREF, and RBD models, the resulting log likelihoods are -1454 , -1451 , and -1435 , respectively.

TABLE 2
Estimation Results

	G&L Model		NOREF Model		TEMPREF Model		RBD Model	
	coef.	(t-stat)	coef.	(t-stat)	coef.	(t-stat)	coef.	(t-stat)
Marketing Mix Coefficients (β 's)								
Quality	–	–	2.913	(5.19)	2.898	(4.70)	–	–
Price	–2.410	(–12.37)	–2.463	(–13.27)	–	–	–	–
Feature	0.596	(6.08)	0.422	(4.60)	0.453	(4.82)	0.459	(4.92)
QUALGAIN	–	–	–	–	–	–	1.904	(2.27)
PRICEGAIN	–	–	–	–	2.045	(4.10)	1.911	(7.46)
RPRICE	–	–	–	–	–2.430	(–10.62)	–	–
Loss Aversion Parameters (λ 's)								
QUALLOSS	–	–	–	–	–	–	2.695	(7.29) ^b
PRICELOSS	–	–	–	–	1.457	(2.18) ^b	1.660	(5.54) ^b
Loyalty Parameters/brand-specific								
Constants ^a								
Citrus Hill	1.117	(6.60)	0.322	(5.37)	0.299	(5.25)	0.666	(5.01)
Minute Maid	1.068	(5.69)	0.222	(4.44)	0.222	(4.44)	0.479	(4.13)
Regional brand	0.188	(1.11)	0.178	(4.56)	0.171	(4.50)	0.470	(3.95)
Tropicana Regular	0.353	(2.26)	0.170	(4.59)	0.170	(4.47)	0.400	(4.08)
Store brand	0.000	–	0.154	(3.36)	0.148	(3.29)	0.691	(2.90)
Tropicana Premium	0.814	(3.27)	0.055	(2.60)	0.054	(2.57)	0.121	(2.57)
Smoothing Constant (γ)	0.831	(–3.07) ^b	–	–	0.847	(1.74)	–	–
Nonstationarity Parameter (ν)	–	–	0.929	(–7.07) ^b	0.929	(–7.15) ^b	0.954	(–5.07) ^b
Polarization Index (ϕ)	–	–	0.478	–	0.484	–	0.261	–
Calibration Period ($N = 1589$):								
Log Likelihood	–1438	–	–1423	–	–1421	–	–1404	–
Parameters Estimated	9	–	10	–	13	–	12	–
Fit Statistic ($\bar{\rho}^2$) ^c	0.418	–	0.423	–	0.423	–	0.430	–
Forecast Period ($N = 666$):								
Log Likelihood	–621	–	–608	–	–608	–	–606	–
Fit Statistic (ρ^2)	0.370	–	0.384	–	0.384	–	0.385	–

^a For the G&L model, these parameters are brand-specific constants; the value for the store brand is constrained to zero. The logit coefficient for G&L loyalty is 3.928 ($t = 23.59$). For the other models, these parameters are the loyalty parameters (α 's) for the NSDM loyalty measure. As previously mentioned, it is not possible to estimate brand-specific constants when the models contain the quality measure used in this analysis.

^b For these parameter estimates, t -tests are reported for null hypothesis value of 1.0.

^c The $\bar{\rho}^2$ statistic reflects model fit adjusted for the number of estimated parameters: $\bar{\rho}^2 = 1 - (LL^* - K)/LL_0$, where LL^* is the log likelihood for the model, K is the number of estimated parameters, and LL_0 is the log likelihood for the null model (which, in this case, assumes equal market shares for all brands).

4. Discussion

4.1. Summary

This paper has argued that the traditional analysis of brand choice does not properly address two important concepts: reference dependence and loss aversion. The first emphasizes the role of relative evaluation in choice, the second suggests that this relative evaluation is strongly influenced by product attributes being seen as gains or losses relative to a reference point in the attribute space.

A multinomial logit model specification that incorporates these concepts does a good job of accounting for the orange juice purchases made by a scanner panel. Our four major predictions are confirmed: (1) it has superior fit to a nonreference dependent model in both estimation and prediction; (2) its coefficients are consistent with the notion of loss aversion, with losses relative to a reference brand showing more impact upon choices than gains for both the attributes we have considered, price and quality; (3) it demonstrates decreased cross-sectional heterogeneity and (4) decreased nonstationarity, which we attribute to diminished specification error.

4.2. *Implications for Models of Competition*

We have demonstrated that accounting for the effects of reference dependence and loss aversion can improve our understanding of brand choice. Recognition that these choices also determine aggregate measures of market performance (such as market share) suggests that the concepts of reference dependence and loss aversion also have important implications for understanding competition among brands. Much of the current formal analysis of brand competition assumes reference independence. In light of our results, we suggest that an attractive research stream would be to develop formal analyses of competitive situations, based on an underlying choice process that exhibits reference dependence and loss aversion. We now briefly discuss the application of these two concepts to the study of: (1) the asymmetric effects of price promotions, and (2) the implications from the so-called first-mover advantage.

4.2.1. *Asymmetric Patterns of Price Competition.* An emerging stylized fact is that changes in product characteristics can generate asymmetric consumer responses. Consider, for example, changes in price. One basic result, due to Blattberg and Wisniewski (1989), is that when higher price, higher quality brands promote, they steal share from lower price, lower quality brands, but when the lower price, lower quality brands promote, there is very little switching down by consumers of the higher quality brands. Blattberg and Wisniewski model this as an *aggregate* effect caused by heterogeneity in quality preferences across the population. The degree of asymmetry is affected by the shape of the distribution of quality preferences across the population.

Allenby and Rossi (1991) offer another explanation suggesting that this phenomenon is a household-level income effect induced by the price promotion. Their model relaxes the standard MNL assumption of constant marginal utility of consumption of each brand; nonconstant marginal utility leads to rotating indifference curves, which results in asymmetric switching due to income effects. Such an approach has significant theoretic appeal because it accounts for asymmetries that would otherwise be incompatible with the traditional microeconomic theory of consumer choice.

A third, psychologically motivated explanation can be generated using the basic concepts of loss aversion and reference dependence. The intuition of the loss aversion explanation of asymmetric response to price promotions is illustrated in Figure 2, which portrays part of the orange juice market we have used for our model estimation. For illustrative purposes, we have superimposed linear indifference curves corresponding to the estimates of λ_p and λ_q estimated using the RBD model, and have assumed, for the purposes of this example, that Citrus Hill (CH) is the reference brand for this purchase occasion. We have also positioned two additional brands in the space: Minute Maid (MM), a higher price, higher quality brand, and Tropicana Regular (TR), a lower quality, lower price brand of orange juice. The horizontal arrow represents an equivalent 12 cent price promotion by Minute Maid and Tropicana Regular.⁷

To understand why loss aversion could cause the asymmetric response, notice that Minute Maid is in the sector of the attribute space governed by loss aversion for price, and that a 12 cent price cut is sufficient to move the brand on to the same indifference curve as the reference brand, Citrus Hill. In contrast, Tropicana Regular lies in the sector of the attribute space governed by loss aversion for quality. Since the loss aversion coefficient for quality is much greater than that for price, the equivalent price cut leaves Tropicana Regular still relatively unattractive.⁸

⁷ Note that this is simply a hypothetical example designed to illustrate, rather than analytically prove, the concept being discussed. Actual attribute and loss aversion coefficient values are only used to add realism to the example; the 12 cent price cut discussed *only* applies to this example.

⁸ Contrast this to the standard analysis (e.g., NOREF), which says that any price cut large enough to induce switching from Citrus Hill to Minute Maid would also result in switching from Citrus Hill to Tropicana Regular if the cut were made by Tropicana Regular.

This analysis has a number of interesting implications, several of which serve to separate it from other explanations of asymmetric switching. The first is that the asymmetric response can occur at the individual level (versus the aggregate effect in Blattberg and Wisniewski). Second, we would expect the pattern of asymmetric switching to vary as a function of reference brand, with each brand having a distinctive pattern of asymmetries. Finally, this analysis suggests that similar asymmetric responses would be expected in response to changes in the levels of other product attributes (e.g., a change in product quality).

4.2.2. Market Pioneer Advantage. We now consider the well-documented advantages that early movers seem to have in entering a product class (Urban et al. 1986; Carpenter and Nakamoto 1989, 1990). From a loss aversion perspective, one account of the first mover's advantage is that the first brand to enter a new product class serves as a reference brand for consumers. Any subsequent brand that does not dominate the new entrant would suffer a disadvantage: at least one of its attributes would be a loss relative to the first entrant. While a full analysis of competitive entry from a loss aversion perspective is beyond the limits of this paper, it is clear that such an analysis would suggest that the later entrant should consider the relative loss aversion of the attributes that define the product space. Efforts to minimize the difference between the new entrant and pioneering brands should concentrate on those attributes with the highest degree of loss aversion. A loss aversion perspective would not necessarily agree with the advice of Urban that a new entrant should try to enter with a lower price, since price may well have a fairly low degree of loss aversion. It would however, strongly endorse their suggestion that a new brand introduce a new attribute. The new entrant might then deprive the pioneering brand of its status as reference brand if the new attribute is important. Thus the view of entry that follows from a reference-dependent view of choice could have significant differences from prior analyses.

4.3. Future Research

While models incorporating reference-dependence and loss aversion add further richness to current models of choice, the specific operationalization considered in this paper has several shortcomings. Future work should explore solutions to these problems:

- Our definition of reference brand is obviously imperfect. While it is based on a fairly simple operationalization, improvements may be possible.
- Our model assumes homogeneity in response to marketing mix variables. In addition to picking up loss aversion and reference effects, the price and quality constructs in our model might also be capturing underlying heterogeneity in household response to marketing mix variables. Thus, a natural extension of our model is to explicitly allow for heterogeneity in response to marketing mix variables. Possible approaches include random coefficient models (e.g., Gonul and Srinivasan 1993) or finite mixture models (e.g., Bucklin and Gupta 1992, Kamakura and Russell 1989). Work by Bell and Lattin (1993) suggests that estimates of the loss aversion coefficients (λ) will decrease when such heterogeneity is modeled explicitly.
- In addition to assuming homogeneity in response to marketing mix variables, our model also assumes homogeneity in the loss aversion coefficients λ for each attribute. It would be interesting to allow these coefficients to vary across households. While we suspect that some of the factors associated with the degree of loss aversion are common across individuals, others may be individual specific.
- The individual attribute value functions we use are linear; an extension would be to use a nonlinear function, say a power function, that would allow us to formally test for the presence of diminishing sensitivity.

At a more general level, we should make it clear that both relative and absolute evaluations must play a role in consumer choice. Several models currently do this, most

recently the relative advantage model of Tversky and Simonson (1993). An important methodological goal would be the estimation of models incorporating both components of choice. Conceptually, a more important goal would be an understanding of the comparable roles of absolute and relative evaluation in choice.

A final set of interesting issues surround the application of the notions of reference dependence and loss aversion to brand competition. We have sketched two such extensions, but feel there is potential for many more applications. We are particularly interested in the implications of loss aversion and reference dependence to strategic issues surrounding product design and strategy.⁹

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⁹ This paper was received October 11, 1991, and has been with the authors 7 months for 2 revisions. Processed by Imran S. Currim, former Area Editor.

Appendix 1: Overview of NSDM Loyalty Measure

This appendix briefly describes the nonstationary Dirichlet-multinomial (NSDM) loyalty variable. A more complete description can be found in Fader and Lattin (1993).

The NSDM model operates under the premise that brand preferences are characterized by relatively long periods of stationarity that are interrupted by occasional shocks (or renewals), at which times a household draws a new set of brand preferences and starts the process once again. During stationary periods, preferences follow the Dirichlet-multinomial (DM) model (Goodhardt, et al. 1984; Fader 1993), which has the following structure:

$$DM_{hjt} = \frac{\alpha_j + \sum_{c=1}^{t-1} y_{hjc}}{S + n_{ht}}, \quad \text{where} \quad (A1)$$

DM_{hjt} = DM preference for brand j by household h on purchase occasion t ,

α_j = brand-specific preference parameter,

$S = \sum_j \alpha_j$,

$y_{hjc} = 1$ if household h buys brand j on purchase occasion c , 0 otherwise, and

$n_{ht} = \sum_j \sum_c y_{hjc}$ = the total number of purchases by household h up to (but not including) purchase occasion t .

The timing of renewals is governed by a geometric process. At any given purchase occasion there is a constant probability ν that the household of interest simply retains its set of preference parameters and continues with its ongoing stationary DM process. But with probability $(1 - \nu)$, the household will undergo a renewal. In such a case, the household abandons or "forgets" all of its past choices and begins the stationary DM process again with $DM_{hjt} = \alpha_j / S$.

Consider, for example, the NSDM preference for a household at its third purchase occasion:

$$NSDM_{hj3} = (1 - \nu) \frac{\alpha_j}{S} + \nu(1 - \nu) \frac{\alpha_j + y_{hj2}}{S + 1} + \nu^2 \frac{\alpha_j + y_{hj1} + y_{hj2}}{S + 2}. \quad (A2)$$

The first term on the right refers to the situation (occurring with probability $(1 - \nu)$) that a renewal took place between the second and third purchases, whereas the last term on the right represents the contingency that no renewals have taken place since the first purchase was made.

Fader and Lattin (1993) offer further background and theoretical justification for this loyalty measure, demonstrate its strong empirical performance, and discuss the useful interpretations associated with its parameters.

Appendix 2

In this appendix we describe and compare five different methods of generating reference brands at each purchase occasion.

Method 1. The simplest approach is to use the same brand as reference brand for all purchase occasions. The most logical choice would be Citrus Hill, which has the highest market share of the six brands in this dataset.

TABLE A1
Comparison of Methods to Generate Reference Brands

	Method 1	Method 2	Method 3	Method 4	Method 5
Log Likelihood	-1421	-1419	-1417	-1414	-1404
Heterogeneity (ϕ)	0.475	0.462	0.432	0.390	0.261
Nonstationarity (ν)	0.925	0.924	0.924	0.930	0.954

See Appendix 2 for descriptions of each method.

Method 2. One household-level approach is to determine the most frequently purchased brand for each household over the initialization period and use this brand as the household’s reference brand through the rest of its purchase history.

Method 3. A natural way to broaden method 2 is to extend it into the calibration period. That is, each household’s reference brand at purchase occasion t is the brand most frequently chosen by that household across all of its purchase occasions up to (but not including) purchase occasion t .

Method 4. A further generalization is to use the brand with *maximum loyalty* at purchase occasion t , instead of just the most frequently purchased, as the reference brand. This weights recent purchases more highly than remote purchases and also accounts for differences in brand availability.

Method 5. Last brand chosen.

For methods 2 through 5, if the calculated reference brand is unavailable at any given purchase occasion, we use the available brand with maximum loyalty as reference brand instead. Table A1 summarizes the key summary statistics for RBD models using each of these different procedures.

These results show strong support for the chosen method. Observe that the changes in estimated levels of heterogeneity and nonstationarity are consistent with the hypotheses discussed earlier: better reference-brand-generating methods (as judged by calibration log likelihood) tend to lead to lower estimates of heterogeneity and nonstationarity.

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