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ABSTRACT

Using the brand last chosen as a reference point, we empirically investigate the role played by multiattribute reference points in the evaluations that underlie brand consideration and brand choice. The results establish that reference dependence effects are present in evaluations, but the nature of those effects differs by task (brand consideration versus brand choice) and by consumer. When considering brands, frequent buyers seek gains in quality while infrequent buyers focus on avoiding losses in quality (quality loss aversion). However, when it comes to actually choosing a brand, all buyers focus on avoiding losses in terms of price (price loss aversion). We discuss these results as a basis for market segmentation.

Introduction

There is much experimental evidence and field research indicating that consumers evaluate product attributes relative to reference points rather than in an absolute sense. In other words, consumers weigh alternatives in terms of attribute gains and losses rather than specific amounts. Substantial research has shown that in those evaluations, losses are weighed more heavily than equivalent-sized gains, a property known as loss aversion.[1]

At the micro level, this reference dependence in brand evaluations is fundamental to understanding individual consumer behavior. Observed behavioral tendencies such as the endowment effect, the status quo bias, and preference reversals have all been linked to the use of multiattribute reference points and the loss aversion property (for a discussion, see Tversky and Kahneman 1991). At the macro level, reference dependence effects have been linked to asymmetric competition (Hardie, Johnson, and Fader 1993, Bronnenberg and Wathieu 1997) dynamic pricing (Kopalle, Rao, and Assunção 1996), and category purchase decisions (Bell and Bucklin 1999). Unquestionably, to fully understand individual behavior as well as aggregate market response we must take reference dependence effects into account. A comprehensive understanding of the issue is essential to efficient marketing.

Nonetheless, despite the pivotal role of reference dependence effects, research has not always recognized the natural context in which consumer behavior is played out. One omission in particular stands out: research on reference dependence focuses almost exclusively on choices from exogenously-determined consideration (or choice) sets,[2] and thus the possible role of multiattribute reference points in determining brands for consideration remains unknown.

Furthermore, the research generally assumes that the impact of reference dependence on brand evaluations is identical across consumers. Empirical evidence to the contrary is limited (Krishnamurthi et. al. 1992 and Briesch et. al. 1997). Hardie, Johnson, and Fader (1993) argue that the specification of idiosyncratic multiattribute reference points suffices to capture consumer heterogeneity in brand choice. Bell and Lattin (1996) emphasize the importance of considering consumer heterogeneity but also argue that it is the heterogeneity itself that gives rise to significant reference dependence effects. For example, they argue that since price-sensitive consumers on average pay a lower price, they have lower reference points and thus experience a greater number of losses; less price-sensitive consumers, on the other hand, typically pay higher prices and thus encounter a larger number of gains. Hence, higher sensitivity in the domain of losses may in part be due to cross-sectional heterogeneity in price sensitivity rather than to the individual consumer weighing losses more heavily than gains. This argument holds, of course, only so long as all consumers consider all brands. However, we know this is not the case. What happens, for example, if price sensitivity also underlies brand consideration, with price-sensitive consumers only having low-priced brands in their consideration sets and less price-sensitive consumers only having higher priced brands in their consideration sets? A comprehensive empirical test of consumer heterogeneity in reference dependence effects in the context of idiosyncratic consideration sets is currently lacking in the literature.

These shortcomings are significant for marketing. Managers worry about whether or not their brands are members in the consideration sets of consumers, and what they can do to influence or assure membership. Characterizing and understanding consumer heterogeneity is at the core of marketing. It forms the basis for market segmentation and as such enables marketers to develop more efficient marketing programs. The goal of this paper is thus to answer two questions: First, are the brand evaluations that underlie consideration set formation characterized by reference dependence effects and, if so, do these evaluations exhibit loss aversion? Second, are consumers heterogeneous in the asymmetry of gains and losses in evaluations underlying brand consideration set formation and brand choice? Hence, the objective is to shed light on the heterogeneity of consumers and tasks (brand consideration versus brand choice) in reference effects and loss aversion.

To address these questions, we developed a modeling framework relying on ex ante literature for specification and operationalization. The calibration of the models was done on a unique data set. Using a computer-assisted shopping task, we were able over time to collect consideration and choice data from 142 participating consumers for a frequently-purchased, non-durable product category. The key findings in this paper are that:

(a) reference dependence plays a role in both brand consideration and brand choice. Accordingly, consideration sets are formed around, and in reference to, the brand last chosen;

(b) there is heterogeneity in reference dependence in terms of brand consideration, but homogeneity in terms of brand choice. While all consumers exhibit loss aversion in choice, there is both loss aversion and gain seeking in consideration. Accordingly, reference points affect preference structures differently across tasks (brand choice versus brand consideration) and across consumers (particularly in the consideration domain). Ignoring the role of brand consideration leads to the false belief that consumers are homogeneous; and

(c) reference dependence occurs on different dimensions across tasks. The results show that reference dependence in terms of brand consideration is entirely in the domain of perceived quality while in terms of choice it is in the domain of actual price. Accordingly, since consideration precedes choice, it is crucial for marketers to understand consumer heterogeneity in the domain of perceived quality.

The paper proceeds as follows: First, we introduce the models and their operationalization. Second, we discuss the unique data set. Third, we report the calibration and validation results. Fourth, we discuss the use of the results as a basis for market segmentation. We conclude with a discussion and some suggestions of avenues for future research.

Modeling and Operationalization

In modeling the sequential tasks of brand consideration and choice, we follow ex ante literature and specify a threshold model for brand consideration and a multinomial logit model for brand choice. Since our unique data set contains consideration set data as well as choice data, we can estimate both models independently; more importantly, and more reflective of the true nature of a two-stage choice process, we can estimate the brand choice model with the benefit of knowing the consideration set membership. We first discuss the general structure of the proposed models and subsequently detail their operationalization.

Threshold models have become widely accepted in modeling consideration set formation (e.g., Fader and McAlister 1990, Inman, McAlister, and Hoyer 1990, Roberts and Lattin 1991, Andrews and Srinivasan 1995, Bronnenberg and Vanhonacker 1996). The principle of these models is that a brand's salience has to exceed a threshold for that brand to be considered. Specifically, the probability that brand i is in consumer h's consideration set at time t equals

$$P(\text{Brand } i \in C_t^h) = P\left(s_{it}^h > \tau_t^h\right) \qquad (1)$$

where s_{it}^h denotes brand i's salience for consumer h at time t, τ_t^h denotes an individual and category-specific salience threshold at time t, and C_t^h denotes the consideration set of consumer h at time t. We postulate that a brand's salience can be captured in a linear additive function, or

$$s_{it}^h = \gamma_{oi} + \gamma' z_{it}^h + \delta_{it}^h \qquad i = 1, 2, \ldots, n \qquad (2)$$

where γ_{oi} denotes a stationary and homogeneous base salience for brand i, z_{it}^h denotes a vector of exogenous variables affecting brand i's salience for consumer h at time t, γ denotes a parameter vector capturing the effect of those variables on brand i's salience, n denotes the number of brands in the category of interest, and δ_{it}^h denotes a random component. We postulate that the salience threshold consists of a deterministic and a random component, or

$$\tau_t^h = t_t^h + \delta_{n+1,t}^h .$$

Assuming that the (n+1) random components δ_{it}^h are iid draws from a Type-1 Extreme Value distribution, the consideration set inclusion probability in (1) can be expressed as

$$P(\text{Brand } i \in C_t^h) = 1/\left[1 + \exp\left(t_t^h - \left(\gamma_{oi} + \gamma' z_{it}^h\right)\right)\right]. \qquad (3)$$

with components as defined above. Expression (3) represents the basic threshold model used in this research. The operationalization of z_{it}^h is discussed momentarily. We first introduce the brand choice model.

Brand choice is modeled as a standard multinomial logit model where the probability that consumer h will choose brand i at time t is expressed as

$$P_{it}^{h} = \frac{\exp(v_{it}^{h})}{\sum_{j \in C_t^h} \exp(v_{jt}^{h})} \tag{4}$$

where v_{it}^{h} denotes the deterministic component of the standard random utility function; i.e., $u_{it}^{h} = v_{it}^{h} + \mu_{it}^{h}$ where μ_{it}^{h} is the random utility component. Assuming the n random components μ_{it}^{h} are iid draws from a Type-1 Extreme Value distribution, utility maximization over the brands in the consideration set results in expression (4) (McFadden 1974). Following prior research, v_{it}^{h} is specified as a linear additive function, or

$$v_{it} = \alpha_{io} + \alpha' x_{it}^{h} \tag{5}$$

where α_{io} is a brand-specific constant capturing a homogeneous, intrinsic brand preference, x_{it}^{h} denotes a vector of exogenous variables affecting the utility that consumer h attaches to brand i at time t, and α denotes a parameter vector capturing the effect of those variables on the utility of brand i for consumer h.

Both z_{it}^{h} in (3) and v_{it}^{h} in (4) are operationalized identically as linear additive functions of brand loyalty and price/quality reference dependence. For brand loyalty, we follow Guadagni and Little (1983) and define the measure

$$LOY_{it}^{h} = \lambda^{loy} LOY_{it-1}^{h} + (1 - \lambda^{loy}) D_{it-1}^{h}$$

where $D_{it-1}^{h} = 1$ if brand i was chosen at t-1 by consumer h, and $D_{it-1}^{h} = 0$ if otherwise. λ^{loy}, with $0 < \lambda^{loy} < 1$, is a smoothing parameter to be estimated. Although the brand loyalty variable captures state dependence in choice, it has also been viewed as capturing consumer heterogeneity because of its idiosyncratic character (e.g., Chintagunta, Jain, and Vilcassim 1991, Jones and Landwehr 1988). Given our interest in heterogeneity, we integrate the variable into our model.

Reference dependence in the price/quality domain is operationalized here as in Hardie, Johnson, and Fader (1993). First, we use the brand chosen at t-1 as the reference brand, but we use the actual price at t as the reference point. Hence, consistent with empirical evidence that consumers cannot recall prices they paid for items purchased in the past (Dickson and Sawyer 1990), we assume that consumers remember the *brand* they bought at t-1 but they will use its *current actual price* as the reference point. In other words, apart from *which* brand is the reference brand, reference dependence is purely a cross-sectional evaluation at time t. As discussed in Hardie, Johnson, and Fader (1993), the selection of the brand last chosen as the reference brand is intuitive and fits with the status-quo phenomenon implied by reference dependence. Furthermore, this selection implies that at the aggregate level the market shares (or more specifically the choice shares) at t-1 represent the distribution of reference points across consumers at time t,[3] which is important for managerial insight and interpretation. Accordingly, we create four variables to capture reference dependence in the price/quality domain, and those variables are defined as:

PG_{it}^{h} = max (0, the actual price of the reference brand for consumer h at time t - the actual price of brand i at time t);

PL_{it}^{h} = min (0, the actual price of the reference brand for consumer h at time t - the actual price of brand i at time t);

QG_{it}^{h} = max (0, the perceived quality of brand i for consumer h at time t - the perceived quality of the reference brand for consumer h at time t); and

QL_{it}^{h} = min (0, the perceived quality of brand i for consumer h at time t - the perceived quality of the reference brand for consumer h at time t).

Note that all four variables are time-dependent and individual-specific. Moreover, brand salience in (2) is operationalized as

$$s_{it}^{h} = \gamma_{oi} + \gamma_1 LOY_{it}^{h} + \gamma_2 \left[PG_{it}^{h} + \lambda_p^s PL_{it}^{h}\right] + \gamma_3 \left[QG_{it}^{h} + \lambda_q^s QL_{it}^{h}\right] + \delta_{it}^{h} \qquad (6)$$

where λ_q^s and λ_p^s are the loss aversion parameters for quality and price, respectively.

Brand utility in (5) is operationalized as

$$v_{it}^h = \alpha_{io} + \alpha_1 LOY_{it}^h + \alpha_2 \left[PG_{it}^h + \lambda_p^v PL_{it}^h\right] + \alpha_3 \left[QG_{it}^h + \lambda_q^v QL_{it}^h\right] \tag{7}$$

where λ_q^v and λ_p^v are the loss aversion parameters for quality and price. Accordingly, when the lambda parameters are different from one, we have reference dependence, while values larger than one imply loss aversion (Hardie, Johnson, and Fader 1993).[4]

Given our interest in consumer heterogeneity, we should emphasize the idiosyncratic nature of all exogenous variables specified in (6) and (7). By the very nature of their measurement, discussed momentarily, the quality perceptions of the brands are idiosyncratic and, hence, different across consumers. The operationalization of the reference brands (i.e., the brands last chosen) and the state dependence in the loyalty variable give rise to gain/loss variables and a brand loyalty variable, respectively, which differ across consumers at each purchase occasion. As for the model parameters, we do not consider intrinsic preference heterogeneity (i.e., heterogeneity in the α_{oi}'s in (6)) or intrinsic basic salience heterogeneity (i.e., heterogeneity in the γ_{oi}'s in (5)). As Chintagunta, Jain, and Vilcassim (1991) discuss, these types of heterogeneity raise difficulties in estimation when combined with heterogeneity in response parameters. We pursue heterogeneity in the response parameters using a latent segmentation estimation approach (Kamakura and Russell 1989).

The Data Set

The data used in this study were collected through a computer-assisted choice task conducted in Hong Kong. Through a posted ad explaining the format of the shopping task, 160 shoppers were recruited to participate in an experiment lasting four weeks. On Monday and Thursday of each week, the participants were given a computer diskette that contained an interactive shopping trip program. They were given access to computers and asked to perform a simulated shopping task for beer. The diskettes were collected on the following

Tuesday or Friday, respectively. The 142 participants who completed the 8 simulated trips received HK$60 (about US$8) for their participation.

The nine brands of beer that were included in the study were the most popular brands in the geographic area where the task was conducted. On each trip, participants were given brand names, regular prices, price discounts (if any), and the actual prices (i.e., regular price minus the discount). Regular prices were the mean prices obtained through a store check in the area. Discounts were determined randomly with probabilities equal to 0.40 for no discount and 0.15 for 4 levels of commonly observed price discounts of HK$1.5, 1.0, 0.7, and 0.3. The order of presentation of all information was automatically randomized.

On each shopping trip, participants were asked to indicate which brands they considered seriously, i.e., the consideration set, and which brand they chose to purchase from that set. This information was solicited as follows: on each occasion, we showed a table with the brand names, regular prices, discounts, and actual prices of the nine brands, and for each of the brands asked, "Would you seriously consider brand X for purchase?" After the respondent finished the consideration task, we showed a table containing the considered brands. Below the table, we asked the question, "Which brand do you want to purchase?" Three weeks into the experiment, after the 6th shopping trip was completed, participants were asked about their perceptions of the brands' quality on a 6-point scale (low quality=1 and high quality=6).

Prior to the experiment, some socio-economic and demographic information was collected. The profile of the 142 participants who completed the 8 simulated trips was as follows: the average age was 30.5 years (ranging from 18 to 60); the male to female ratio was 18.5% to 81.5%; the ratio of married to unmarried was 49.7% to 50.3%; the average family size was 4.45 (ranging from 1 to 13); 72.2% of the participants had a monthly income between HK$10,000 to 20,000; 53.6% of the participants owned their own homes or apartments; and 43.7% had attained a high school education or lower while 38.5% had a college or higher degree.

Table 1 gives an overview of the shopping task data. The regular prices indicate that the nine brands belong to three price tiers: high-priced brands with prices ranging from HK$7.90 to HK$8.10 (Blue Ice, Heineken, and Corona), medium-priced brands with prices ranging from

Table 1

Overview of Data

Brand	Regular Price [a]	Average Actual Price [a]	Average Discount [a]	Average Perceived Quality [b]	Consideration Set Share [c] (%)	Choice Share (%)
San Miguel	5.40	4.90	0.50	3.60 (1.06)	48.6	20.0
Carlsberg	6.50	5.98	0.52	3.89 (1.10)	56.9	21.9
Blue Ice	7.90	7.41	0.49	3.54 (1.00)	18.1	3.1
Kirin	6.50	6.00	0.50	3.42 (1.06)	14.4	1.7
Tsing Tao	6.40	5.90	0 50	3.47 (1.27)	39.0	10.6
Budweiser	6.30	5.74	0.56	3.37 (0.98)	17.8	2.7
Blue Ribbon	4.90	4.41	0.49	3.54 (1.10)	40.3	14.4
Heineken	8.10	7.55	0.55	4.13 (1.27)	44.5	22.2
Corona	8.10	7.56	0.54	3.35 (1.07)	12.1	3.4

[a] Expressed in HK$ (7.78HK$=1US$); for one can of beer.
[b] Measured on a 6-point scale (low quality=1; high quality=6) with standard deviations in parentheses.
[c] Over the purchase occasions, the percentage of times an average consumer considered the brand for purchase.

HK$6.30 to HK$6.50 (Carlsberg, Kirin, Tsing Tao, and Budweiser), and low-priced brands with prices ranging from HK$4.90 to HK$5.40 (San Miguel and Blue Ribbon). On perceived quality, Heineken and Carlsberg stand out from the others, and the two brands account for a 44.1% choice share relative to a 35.2% consideration share. Table 2 gives the frequency distribution of the consideration set sizes. Where the modal value is close to two, the mean value is close to three. In 27.1% of the purchase occasions instances the consideration set contained only one brand.

Calibration and Validation Results

The total sample of 142 participating consumers was randomly split into an estimation sample (105 consumers) and a holdout sample (37 consumers). Using the estimation sample, the consideration model and the choice model were calibrated both with and without reference dependence effects in the price/quality domain. Recognizing possible heterogeneity in those effects and other response parameters, the calibration was done using a latent segmentation approach (Kamakura and Russell 1989). To avoid parameter instability when multiple segments were considered, the brand loyalty variable was operationalized assuming a homogeneous smoothing parameter equal to the single-segment λ^{loy} parameter estimate. The results for the consideration model are shown in Table 3 and those for the choice model are shown in Table 4.

Following the arguments provided in Allenby (1989) and Bucklin and Gupta (1992), we relied on the BIC criterion to select the number of segments. Accordingly, the consideration model results in Table 3 suggest a three-segment solution when reference dependence effects are specified, and a two-segment solution when they are not. The likelihood ratio test comparing these two models equals χ^2=482.2 (19 degrees of freedom) which is significant at α=0.05. Hence, there is significant support for reference dependence effects in brand consideration. Furthermore, the three-segment solution indicates the presence of consumer heterogeneity in the price/quality reference dependence effects. The precise nature of that heterogeneity will be discussed momentarily.

For the choice model, the BIC results in Table 4 indicate that a single-segment solution is superior in fit for both the model with reference dependence effects and the one without these

Table 2

Frequency (%) Distribution of Consideration Set Sizes [a]

Number of Brands in Consideration Set	Frequency	Cumulative
1	27.1	-
2	19.5	46.6
3	20.5	67.1
4	14.8	81.9
5	9.6	91.5
6	5.4	96.9
7	1.7	98.6
8	0.2	98.8
9	1.2	100.0

[a] Mean size equals 2.91.

Table 3

Fit Statistics for Consideration Model [a]

	Reference Independence				Reference Dependence			
	One Segment	Two Segments	Three Segments	Four Segments	One Segment	Two Segments	Three Segments	Four Segments
Fit Statistics [b]								
LL	-3000.2	-2936.5	-2936.5	-2936.5	-3061.3	-2806.7	-2695.4	-2634.6
$\bar{\rho}^2$	0.343	0.354	0.351	0.348	0.329	0.382	0.412	0.425
BIC	-3057.4	-3046.5	-3103.6	-3160.8	-3127.3	-2934.3	-2888.9	-2894.6
Number of Parameters (k)	13	25	38	51	15	29	44	59

[a] Estimation sample of 105 households, 735 purchase occasions, 6615 consideration observations.

[b] LL–maximum value of the log likelihood; $\bar{\rho}^2 = 1-(LL-k/LL_0)$ where LL_0 is the log likelihood of the null model which, in this case, assumes a 50/50 chance of each brand being considered (or LL_0=-4585.2); BIC=LL-(k/2) ln (# of observations).

Table 4

Fit Statistics for Choice Model [a]

	Reference Independence				Reference Dependence			
	One Segment	Two Segments	Three Segments	Four Segments	One Segment	Two Segments	Three Segments	Four Segments
Fit Statistics [b]								
LL	-458.3	-439.8	-431.6	-423.4	-448.4	-434.0	-410.4	-402.6
$\bar{\rho}^2$	0.268	0.278	0.272	0.266	0.278	0.281	0.296	0.286
BIC	-497.9	-515.7	-547.1	-578.5	-494.6	-523.1	-545.7	-584.1
Number of Parameters (k)	12	23	35	47	14	27	41	55

[a] Estimation sample of 105 households, 735 purchase observations.

[b] LL=maximum value of the log likelihood; $\bar{\rho}^2 = 1 - (LL - k/LL_o)$ where LL_o is the log likelihood of the null model which, in this case, assumes equal market shares for the brands in the consideration set (i.e., $LL_o = -640.8$); BIC = LL-(k/2) ln (# of observations).

effects. Comparing both single-segment solutions, the likelihood ratio test equals χ^2=19.8 (2 degrees of freedom) which is significant at α=0.05. Accordingly, there is significant support for reference dependence effects in brand choice but, in contrast to the effects identified in consideration, those effects appear to be homogeneous across consumers.

In sum, the model-fit statistics reported so far indicate that reference dependence effects as defined above occur in the brand evaluations underlying consideration and choice. More importantly, those reference dependence effects appear to be heterogeneous across consumers in consideration but homogeneous across consumers in choice. Hence, there is task (consideration versus choice) as well as consumer heterogeneity in price/quality reference dependence effects. We now detail more precisely the nature of that heterogeneity.

The parameter estimates for the superior-fitting, three-segment consideration model are shown in Table 5. Focusing on the reference dependence effects, we observe that across the three segments none of the price parameters are significant, which suggests that actual price does not play a role in evaluating beer brands for consideration. For perceived quality, however, we do obtain significant parameter estimates for two out of the three segments. In the third segment, which contains 30% of the participating consumers, perceived quality does not play a role in consideration evaluations. For the first segment, the quality loss parameter equals 0.530. Testing this value against H_0: $\lambda_q^s = 1$, it is found that t = -3.015, which is significant at α = 0.05. Accordingly, this segment, which contains 20% of the participating consumers, exhibits quality gain seeking in brand consideration. For the second segment, which contains half of the participating consumers, the quality loss parameter equals 2.035. Testing this value against H_0: $\lambda_q^s = 1$, it is found that t = 1.373, which is significant at α = 0.20. Accordingly, we find some support for quality loss aversion in this segment. In sum, the results in Table 5 indicate significant but heterogeneous reference dependence effects in perceived quality when brands are evaluated for consideration.

The parameter estimates for the superior-fitting choice model are shown in Table 6. The quality gain/loss parameters are both insignificant at α = 0.05. Accordingly, and in contrast to the brand consideration task that precedes choice, perceived brand quality does not play a role in choice. The price gain/loss parameters reported in Table 6 are highly significant, with

Table 5

Estimation Results: Consideration Model With Reference Dependence [a]

	Segment 1	Segment 2	Segment 3
Brand Specific Constants:			
San Miguel	-2.834 (-5.0) [b]	-1.649 (-7.8)	-1.062 (-4.5)
Carlsberg	-2.090 (-3.5)	-1.081 (-5.2)	-1.020 (-4.5)
Blue Ice	-2.796 (-5.0)	-2.064 (-8.6)	-1.976 (-8.2)
Kirin	-3.656 (-6.8)	-3.303 (-10.6)	-1.415 (-6.2)
Tsing Tao	-1.976 (-4.0)	-1.664 (-7.7)	-1.154 (-4.7)
Budweiser	-4.147 (-5.5)	-2.970 (-12.3)	-1.281 (-5.7)
Blue Ribbon	-1.533 (-2.8)	-2.144 (-10.2)	-0.923 (-3.4)
Heineken	-2.874 (-4.2)	-1.619 (-6.2)	-1.089 (-4.2)
Corona	-2.896 (-5.0)	-3.254 (-8.1)	-2.149 (-8.6)
Brand Loyalty	40.590 (8.3)	11.456 (13.0)	12.110 (8.9)
Price Gain	ns	ns	ns
Price Loss (λ_p^s)	ns	ns	ns
Quality Gain	3.630 (3.5)	0.380 (3.3)	ns
Quality Loss (λ_q^s)	0.530 (3.4)	2.035 (2.7)	ns
Segment Size [c]	0.20	0.50	0.30

[a] ns indicates parameters are not significant at $\alpha = 0.05$; $\lambda^{loy} = 0.938$.
[b] t-values in parentheses.
[c] derived from the estimated segment membership coefficients.

Table 6

Estimation Results: Choice Model With Reference Dependence [a]

Brand Specific Constants:	
San Miguel	-1.487 (-3.2) [b]
Carlsberg	-1.358 (-3.3)
Blue Ice	ns
Kirin	-1.791 (-3.5)
Tsing Tao	-1.364 (-3.2)
Budweiser	-1.941 (-3.9)
Blue Ribbon	-2.158 (-4.3)
Heineken	ns
Corona	0000
Brand Loyalty	5.102 (3.7)
Price Gain	0.556 (4.1)
Price Loss (λ_p^v)	1.874 (4.6)
Quality Gain	ns
Quality Loss (λ_q^v)	ns

[a] ns indicates parameters are not significant at $\alpha = 0.05$; $\lambda^{loy} = 0.890$.
[b] t-values in parentheses.

the price loss parameter being equal to 1.874. Testing this value against H_o: $\lambda_p^v = 1$, it is found that t = 2.14, which is significant at $\alpha = 0.05$. Accordingly, we find strong support for homogeneous price loss aversion in the brand choice task.

As a benchmark pertaining to the typical situation where we do not have data on consumers' consideration sets (in working with supermarket scanner data, for example, we only observe choices made), we estimated the multinomial logit choice model with C_t^h equal to the universal set of 9 brands. In specification, this model is identical to the one estimated and reported in Hardie, Johnson, and Fader (1993). Using a latent segmentation estimation approach,[5] the BIC criterion favors a single-segment model with significant price loss aversion ($\lambda_p^v = 1.592$ with t = 2.753 for H_o: $\lambda_p^v = 1$) and significant quality loss aversion ($\lambda_q^v =$ 3.431 with t = 1.266 for H_o: $\lambda_q^v = 1$). On the one hand, these results lend support to Hardie, Johnson, and Fader's (1993) argument that specifying reference dependence reduces consumer heterogeneity. On the other hand, these results do not reveal the heterogeneity in quality reference dependence effects in terms of consideration, which we obtained above. Clearly, knowing the consideration set and incorporating that information into the estimation of the choice model enables a more accurate and substantively insightful recovery of the true role of price/quality reference points in brand evaluations. Not integrating consideration set data drives the estimation towards homogeneous reference dependence effects.

Before discussing in more detail the substantive insights of the calibration results, we report on their reliability and validity. A test-retest reliability check was performed with a randomly selected sample of 70 participating consumers drawn from the entire sample. The selected choice and consideration models were re-estimated on the data for those 70 consumers. The fit statistics for those models are summarized in Table 7. As shown there, the BIC criterion identifies the three-segment solution for the consideration model and the single-segment solution for the choice model, similar to the calibration results reported above.

For the validity check, we used the estimation-sample parameter estimates for the selected models and computed model-fit statistics and hit rates for the holdout sample of 37 participating consumers. For the consideration model, the relative segment sizes were used as prior probabilities of segment membership. The fit results of the validity check are shown in Table 8, and the hit rates are shown in Table 9. For brand consideration, the BIC results in

Table 7

Test-Retest Reliability [a]

Model	Statistics [b]	One Segment	Reference Dependence Two Segments	Three Segments	Four Segments
Consideration Model	LL	-1983.4	-1856.9	-1790.0	-1771.5
	$\bar{\rho}^2$	0.346	0.383	0.400	0.401
	BIC	-2046.0	-1978.6	-1974.6	-2019.1
	Number of parameters (k)	15	29	44	59
Choice Model	LL	-292.4	-271.0	-262.1	-246.1
	$\bar{\rho}^2$	0.279	0.299	0.287	0.292
	BIC	-335.8	-354.6	-389.1	-416.4
	Number of parameters (k)	14	27	41	55

[a] Based on a random sample of 70 participating consumers.

[b] LL = maximum value of the log likelihood; $\bar{\rho}^2 = 1 - (LL\text{-}k/LL_0)$ where LL_0 is the log likelihood of the null model and k denotes the number of parameters; BIC= LL - (k/2) ln (# of observations).

Table 8

Model Validation Statistics [a]

Model	Statistics [b]	Reference Independence	Reference Dependence
Consideration Model [c]	LL_0	-1615.7	-1615.7
	LL	-1156.3	-1080.3
	$\bar{\rho}^2$	0.269	0.304
	BIC	-1253.2	-1250.9
	Number of parameters (k)	25	44
Choice Model [d]	LL_0	-216.5	-216.5
	LL	-139.6	-136.8
	$\bar{\rho}^2$	0.304	0.308
	BIC	-172.9	-175.7
	Number of parameters (k)	12	14

[a] Based on a holdout sample of 37 participating consumers (i.e., 259 observations for the choice model and 2331 observations for the consideration model).

[b] LL_0 is the log likelihood of the null model; LL is the maximum value of the log likelihood; $\bar{\rho}^2 = 1 - (LL - k/ LL_0)$; BIC=LL-(k/2) ln (# of observations).

[c] Applying the 3-segment solution for reference dependence and the 2-segment solution for reference independence.

[d] Applying the 1-segment solution for both reference dependence and reference independence.

Table 9

Validation - Hit Rates [a]

Model		Reference Independence	Reference Dependence
Consideration Model	San Miguel	67.57	62.55
	Carlsberg	65.64	67.57
	Blue Ice	80.69	80.31
	Kirin	81.85	82.24
	Tsing Tao	79.15	74.90
	Budweiser	77.99	77.61
	Blue Ribbon	67.57	66.41
	Heineken	80.31	79.54
	Corona	95.75	95.37
	(Mean)	(77.39)	(76.28)
Choice Model		79.54	81.85

[a] For the consideration model, the relative segment sizes were used as prior probabilities of segment membership (i.e., the probabilities were not updated).

Table 8 favor the reference dependence model validating the results discussed above. For the corresponding hit rates, both models do well and the validity support is less strong; however, the fact that segment membership was not updated might well explain the lack of significant superior performance for the reference dependence model. For the choice model, the BIC results reported in Table 8 weakly favor the reference independence model (a value of -172.9 relative to -175.7 for the reference dependence model selected above). However, the other fit statistics, LL and $\bar{\rho}^2$, favor the reference dependence model as do the corresponding hit rates in Table 9. Overall, given the majority of results that favor the single-segment reference dependence choice model advocated above, we feel comfortable accepting the model's validity. With the test-retest reliability check and the validity check providing confidence in the calibration results reported and discussed above, we turn to the substantive insights provided.

Segmentation

At the aggregate level, the estimation results obtained above revealed three distinct segments in consideration but homogeneity in choice. In other words, consumers evaluate gains and losses differently when creating consideration sets but not when selecting a brand from those sets. The results also indicate that consideration was very much based on perceived quality while choice was very much based on actual price. Hence, looking at the sequential process of consideration and choice and focusing on price/quality response, we have three consumer segments as shown in Table 10. Segment 1, to which 21 participating consumers belong, exhibits quality gain seeking in evaluating beer brands for consideration; when it comes to choosing a brand from the consideration set, they exhibit price loss aversion. Segment 2, to which 53 participating consumers belong, exhibits quality loss aversion in evaluating beer brands for consideration and price loss aversion in choosing a brand from those being considered. Segment 3, to which 31 participating consumers belong, does not exhibit any sensitivity towards either perceived quality or actual price in creating consideration sets; at the time of choice they exhibit price loss aversion.

Using the socio-economic and demographic data on the participating consumers, we ran Duncan tests on means to see if a distinctive profile of the segment members could be identified. The results, based on mean tests significant at $\alpha = 0.05$, are also shown in Table

Table 10

Segmentation Structure
and Membership Profile [a]

	Consideration Task	Choice Task	Consumer Profile [b]
Segment 1 (21)	Quality Gain Seeking	Price Loss Aversion	Loyal in consideration House owners Male Very high purchase frequency Mean consideration set size of 3
Segment 2 (53)	Quality Loss Aversion	Price Loss Aversion	Least loyal in consideration Renters Female Very low purchase frequency Mean consideration set size of 2
Segment 3 (31)	-	Price Loss Aversion	Loyal in consideration Renters Male Low purchase frequency Mean consideration set size over 4

[a] Based on the estimation sample of 105 participating consumers.
[b] Duncan test on means, significant at $\alpha = 0.05$.

10. As can be seen, Segment 1 consumers have high (self-reported) beer purchase frequencies, a mean consideration set size of three, and tend to be male homeowners. Segment 2 consumers have very low beer purchase frequencies, a mean consideration set size of two, and tend to be female renters. Segment 3 consumers have low beer purchase frequencies, a mean consideration set size of four, and tend to be male renters. We can supplement these results by carefully looking at the estimation results in Table 5. As shown there, the corresponding parameter estimates differ quite a bit across the three segments and, hence, cannot be compared directly. However, we can compare ratios. If we divide the brand loyalty parameters by any of the brand-specific constants, we see that the resulting ratio is much higher for Segments 1 and 3 than for Segment 2. Hence, there is some indication that consumers in Segment 2 exhibit less brand loyalty in creating consideration sets. Accordingly, the segment exhibiting quality gain seeking in consideration contains the frequent buyers and, therefore, consumers who are likely more familiar with the category and the brands.

Segment 2, whose consumers exhibit loss aversion in both consideration and choice, have extremely low purchase frequencies. That about half of the participating consumers in the estimation sample belong to this segment reflects the dominance of women in the sample. Because of their low purchase frequencies, these consumers are likely less knowledgeable about the category and the brands, which explains the small consideration set sizes (on average 2 brands) and relatively low loyalty (or state-dependence). What is encouraging for beer marketers is that on average and across the three segments loyalty increases with purchase frequency.

The Segment 3 consumers, whose brand consideration decisions do not involve the price/quality domain, have higher purchase frequencies than Segment 2 consumers (but significantly lower than Segment 1 consumers), however their consideration set sizes are the largest. Perhaps because this segment contains more casual beer drinkers, the larger consideration sets - whose creation we cannot capture in the price/quality domain - might reflect a broader set of social contexts in which these consumers consume beer relatively infrequently. Overall, however, from a volume share perspective, Segment 1 is of crucial importance to beer marketers and, hence, the discovery that these heavy buyers exhibit quality gain seeking in brand consideration and price loss aversion in brand choice underscores the criticality of brand positioning in the price/quality domain.

To supplement these segment profiles, we computed some summary statistics on variables included in this research. Table 11 gives the consideration set shares, choice shares and average perceived quality figures by segment. The significant differences using Duncan tests on the segment means are shown in bold. The average consumer in Segment 1 rates Heineken and Carlsberg of superior quality, considers both more than half of the time, and selects one of these two brands a quarter of the time (with each having a selection probability of almost twice that of San Miguel, the third most frequently chosen brand). What is also interesting to note is that San Miguel and Blue Ribbon have significant choice shares (0.143 and 0.129, respectively) despite being perceived as being inferior in quality to Blue Ice and Corona. All these brands seem to compete for the third spot in the average consideration set, but both San Miguel and Blue Ribbon gain in choice share because of their low price points relative to premium-priced Blue Ice and Corona. Whether or not Blue Ice and Corona would benefit from a lower price point is not immediately evident as their premium-pricing might contribute to their perceived superior quality. However, to the extent that this is true, their premium pricing strategies aid consideration but hurt choice among heavy buyers.

The average consumer in Segment 2 rates Heineken, Carlsberg, and San Miguel higher in quality relative to the other brands[6], considers only Carlsberg more than half of the time (but with San Miguel a close second and Heineken half as often as Carlsberg), and selects San Miguel or Carlsberg slightly more than one quarter of the time (with Heineken having only half of Carlsberg's choice share). Heineken appears to suffer from the fact that on average the Segment 2 consumers consider only two brands and, in contrast to the heavy users of Segment 1, do not exhibit quality gain seeking in brand consideration evaluations.

The average consumer in Segment 3 rates Heineken as superior (and significantly higher than either Carlsberg or San Miguel), but also rates Blue Ribbon, Tsing Tao, and Kirin as superior in quality to San Miguel. The average consumer in this segment considers 5 brands more than 50% of the time (San Miguel, Carlsberg, Tsing Tao, Blue Ribbon, and Heineken), but selects Tsing Tao or Heineken most often, with both having a choice share almost twice that of Blue Ribbon despite the latter having the second highest consideration share (after Heineken).

As we saw in Table 1, three brands (Heineken, Carlsberg, and San Miguel) have choice shares just above 0.20, significantly larger than the next brand (Blue Ribbon with 0.14). In

Table 11

Summary Statistics by Segment [a]

		Segment 1	Segment 2	Segment 3
Perceived Quality	San Miguel	3.381[c]	3.679	3.710
	Carlsberg	3.905	3.849	4.032
	Blue Ice	3.571	3.396	3.871
	Kirin	3.238	3.283	**3.936**
	Tsing Tao	3.381	3.283	**4.194**
	Budweiser	3.238	3.264	3.581
	Blue Ribbon	3.381	3.321	**4.032**
	Heineken	**4.333**	**3.755**	**4.581**
	Corona	3.667	3.170	3.484
Consideration Set Share	San Miguel	0.367[b]	0.442	0.548
	Carlsberg	0.605	0.539	0.594
	Blue Ice	0.259	**0.102**	0.263
	Kirin	0.054	0.040	**0.382**
	Tsing Tao	0.380	0.285	**0.576**
	Budweiser	0.122	0.064	**0.410**
	Blue Ribbon	**0.442**	**0.264**	**0.613**
	Heineken	0.578	**0.275**	0.645
	Corona	0.238	**0.022**	0.212
Choice Share	San Miguel	0.143	0.267	0.157
	Carlsberg	0.252	0.283	0.110
	Blue Ice	0.061	0.022	0.018
	Kirin	0.000	0.008	**0.042**
	Tsing Tao	**0.034**	**0.105**	**0.203**
	Budweiser	0.007	0.027	0.032
	Blue Ribbon	0.129	0.146	0.129
	Heineken	0.265	0.140	0.263
	Corona	**0.108**	**0.003**	**0.046**

[a] Numbers in bold are significant at $\alpha=0.05$.

[b] Over the purchase occasions, an average consumer considered San Miguel 36.7% of the time.

[c] Average perception on a 6-point scale (low quality=1; high quality=6).

Table 11, we note that only Carlsberg and Heineken are consistently perceived as being superior in quality in the three segments. That consistency helps them in entering the consideration set of most consumers. San Miguel is not consistently perceived as being superior in quality, but its low-price point helps it escape the influence of price loss aversion in choice in all three segments. Heineken could benefit from a higher consideration set share in Segment 2, but that would require growing the average consideration set size beyond two brands, since its quality perception is fine. San Miguel would benefit from an improved quality image, particularly among frequent buyers.

Given the relatively high purchase frequencies of consumers in Segment 1, they should form a primary target for beer marketers. To be considered by these consumers, perceived quality is key; indeed these consumers seek out improved quality relative to the brand they purchased on the last occasion. Hence, positioning of an existing or new beer brand in the perceived quality domain is crucial. The brand will enter the consideration set (a necessary but not sufficient condition to be chosen) if consumers perceive it to provide incremental quality above and beyond that of the brand they currently buy. But that added quality cannot be offered at substantially higher price points as consumers exhibit price loss aversion when selecting a brand for purchase. Hence, consideration sets will tend to include brands perceived to be higher in quality, but choice among them will lead towards the selection of the ones with relatively lower price points. Given that consumers restrict the size of their consideration sets, perhaps because of cognitive effort in evaluating brands when a selection has to be made, one might well anticipate an asymmetric shift towards the consideration of higher quality brands over time. What becomes crucial in acting upon these results, but is not dealt with in this research, is to understand what perceived quality means, what it is based on, how it is formed, and how marketers can influence it.

Summary and Future Research

The objective of this research was to answer two questions: First, are the brand evaluations that consumers make while forming consideration sets characterized by reference dependence effects and do they exhibit loss aversion? Second, are those reference dependence effects identical across consumers? As to the first question, the empirical results reported in this paper support the role of reference dependence effects in the brand evaluations that underlie consideration set formation (as well as those underlying choice). As to the second question, the results support cross-sectional heterogeneity in the asymmetry of gains and losses in consideration but not in choice. Contributing to the extensive literature on reference dependence, these results provide initial unique evidence of task and consumer heterogeneity in the area of reference dependence.

Substantively, the identification of consumer heterogeneity has important managerial implications. As a necessary but not sufficient step to brand selection, marketers need to understand perceived quality in order to be able to develop efficient marketing programs based on the segmentation structure revealed in this research. We see this as an important avenue for further research. It is also important to reassess the patterns of asymmetric competition discussed in the literature in light of the consumer heterogeneity identified here. Methodologically, the results show that ignoring or not knowing consideration set membership drives choice model estimates towards homogeneous reference dependence effects.

Footnotes

[1] In the marketing modeling literature, notable references are Lattin and Bucklin (1989), Kalwani et. al. (1990), Kalwani and Yim (1992), Mayhew and Winer (1992), Krishnamurthi et. al. (1992), Kalyanaram and Little (1994), and Briesch et. al. (1997).

[2] We use the term "consideration set" rather liberally to refer to the subset of all available brands that the consumer considers seriously for purchase. Some authors have referred to this subset as the "choice set". Krishamurthi et. al. (1992) also look at purchase quantity decisions in addition to brand choice.

[3] In their empirical investigation of different operationalizations of reference price values using scanner panel data, Briesch et. al. (1997) find the operationalization used here to provide a superior fit in one out of four product categories. In the other three categories, the operationalization does a reasonable job in capturing brand choice.

[4] Some authors (e.g., Kalwani and Yim (1992), Han, Gupta, and Lehmann (1993), and Kalyanaram and Little (1994)) have argued that price gains and losses have to be of a certain magnitude to be noticed and to have an effect on brand utilities. For simplicity, we assume the region of insensitivity (in price and quality) to be zero.

[5] Hardie, Johnson, and Fader (1993) assume response parameter homogeneity.

[6] The range of perceived quality ratings across the nine brands in this segment is markedly smaller than in the other two segments, with mean ratings hovering around the scale midpoint, further suggesting that this segment is comprised of consumers who are less familiar with the category and the brands.

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