BART J. BRONNENBERG and WILFRIED R. VANHONACKER*

It is becoming increasingly evident that a consumer's brand choice decision in low-involvement categories does not involve full search, evaluation, and comparison of price information of all brands available at point of purchase (global price response). The authors propose a two-stage choice process in which the consumer first identifies a subset of brands within the universal set of brands called the *choice set* and then evaluates only those brands that are in the choice set relative to one another to select a single brand. The authors find that, consistent with reports of the extent of external price search of consumers, response to shelf price variations is limited to the brands in the choice set (local price response). Their results indicate that employing the assumption of global price response may lead to biased estimates of price elasticity and derived measures of clout and vulnerability. To enable a managerially meaningful and useful assessment of a brand's competitive clout and vulnerability, the authors provide a brand-level approach to integrate local price response into the derivation of these measures.

Limited Choice Sets, Local Price Response, and Implied Measures of Price Competition

One of the most practical and important questions that brand managers need to answer is whether price changes of their brands on the supermarket shelf influence consumers' choice behavior. Traditionally, this question has been answered through an analysis of price elasticities and derived quantities, such as clout and vulnerability (e.g., Kamakura and Russell 1989). In general, these measures have been assessed with the implicit assumption that a change in price of one brand affects response for all available brands (global price response).

The literature on brand evaluation and external price search, however, provides evidence to the contrary and questions whether all consumers respond to prices of all brands at all purchase occasions. For example, Dickson and Sawyer (1990) show that, for low-involvement categories, external price search of consumers is extremely limited and that as many as 40% of consumers claim that they do not check prices at all. For the remaining consumers, price search appears limited to a small subset of brands and can be influenced by promotion displays, shelf-talkers, and shelf-space allocation (Dickson and Sawyer 1986). Hoyer's (1984) observations of actual behavior of consumers also strongly suggest that consumers only check prices of a limited number of brands in the universal choice set (i.e., the set of all available choice options). Recently, Murthi and Srinivasan (1994) successfully incorporated one important part of the limitations on consumers' extent of evaluation of available brand information into choice models by hypothesizing that consumers evaluate the marketing mix information of all brands only during specific occasions. Our study continues and further develops this tradition by investigating whether, even during specific occasions, consumers evaluate prices of all brands. We find that this is not the case and pursue the implications of this finding with respect to measures of price competition.

We model a two-stage process of *choice set formation* and *brand selection* in an attempt to include the extent of price evaluation into choice models. The fundamental premise of our model is that consumers create a downsized choice set using simple and often noncompensatory rules (Shocker et al. 1991; Urban, Hulland, and Weinberg 1993) and, subse-

*Bart Bronnenberg is Assistant Professor of Marketing, University of Texas at Austin. Wilfried Vanhonacker is Professor of Marketing, University of Science and Technology, Hong Kong, and INSEAD, France.The authors thank Susan M. Broniarczyk, Randolph E. Bucklin, Leigh McAlister, Lung-Fei Lee, Rajendra K. Srivastava and Michael J. Zenor for useful discussions and suggestions. The helpful comments of four anonymous *JMR* reviewers and the *JMR* editor are gratefully acknowledged. The authors extend their appreciation to Geraldine Baretz and Marc Gauguier of Nielsen France for generously providing the data for this study. The first author received financial support from the European Commission and the Sasakawa Peace Foundation.

Journal of Marketing Research
Vol. XXXIII (May 1996), 163–173

quently, restrict evaluation for choice to the brands contained in the choice set. Estimating this model at the segment level using scanner data for laundry detergents suggests that (1) response to price changes of brands appears limited to an occasion-specific subset of brands as opposed to the entire universal set (local price response), (2) our heterogeneous two-stage model seems adequate for tracking and predicting the sets over which consumers are price responsive, (3) a two-segment, two-stage model leads to a better fit and prediction of individual-level choice than does a heterogeneous logit model, and (4) at the brand level, measures of competitive clout and vulnerability obtained by our model are systematically different from those derived from a segment-level logit model. For example, measures of competitive clout of a given brand show a fundamental dependence on the frequency of choice set membership of that brand. Omission of this dependence leads to an overestimation of the measures of competitive clout of as much as 100% in our empirical analysis. A noteworthy auxiliary result from our investigations is that under global price response measures of neither competitive clout nor vulnerability offer any significant information in addition to market share, that is, they are both simple transformations of market share.

After a brief discussion of the relevant literature, we state our assumptions and hypotheses about the choice process and formulate and operationalize our model. Next, we estimate the heterogeneous two-stage choice model along with three benchmark models. In the validation section, first, we compare the predictive validity of the estimated models, and second, we diagnose our model's capacity to differentiate meaningfully between brands that are in the choice set and brands that are not by showing that there is no response to shelf-prices of brands outside the predicted choice set (local price response). Finally, we derive the distribution of occasion-specific choice set sizes at the segment level and conclude by discussing the brand-level measures of clout and vulnerability that are implied by local versus global price response.

BACKGROUND

Relevant Literature

Two-stage choice models consist of a choice set formation stage and a brand selection stage, and for all, choice of a brand is hypothesized to be conditional on that brand being a member of the limited choice set. Although two-stage choice models have been used to study choice among modes of transportation (e.g., Swait 1984), consumer durables (e.g., Urban, Hulland, and Weinberg 1993) and spatial locations (e.g., Meyer and Eagle 1982), most applications involve choices in low-involvement product categories. In the latter realm, research has mainly focused on choice set formation phenomena, such as memory dependence (Alba, Hutchinson, and Lynch 1991), effort and benefit trade-offs (Hauser and Wernerfelt 1990), first-mover advantages (Kardes et al. 1993), the role of shelf-space allocation (Fazio, Powell, and Williams 1989), and in-store cues to raise the accessibility of brands (Nedungadi 1990). Recently, Siddarth, Bucklin, and Morrison (1995) model choice set formation using a Bayesian updating procedure and find that market shares and frequency of choice set membership do not go hand in hand.

The two stages of the choice process are believed to be different in nature. Whereas choice decisions in the final stage of brand selection are thought to be elaborate and compensatory in nature (e.g., Gensch 1987), choice set formation decisions are viewed as arising from more simplistic noncompensatory processes (for a review, see Lehmann and Pan 1994; Shocker et al. 1991; see also Urban, Hulland, and Weinberg 1993).

Hypotheses and Assumptions About the Consumer Choice Process

Choice set formation. Shocker and colleagues (1991) and Nedungadi (1990) proposed that choice set formation in low-involvement categories is rooted in differences of salience across brands. We hypothesize that brand salience is determined by three factors: (1) in-store attempts to make the brand more noticeable, (2) recency of the brand's last purchase, and (3) membership of the brand to the consumer's acceptable price range. We briefly elaborate on each.

First, we hypothesize that brand salience is positively related to in-store attempts to highlight the brand as a choice option, including announcements of price discounts (Alba, Hutchinson, and Lynch 1991; Fazio, Powell, and Williams 1989; Nedungadi 1990). Accordingly, we view part of the choice set formation as a passive (reactive) activity on behalf of the consumer who is influenced by the dynamics of the in-store environment.

Second, we propose that brand salience is related, either positively or negatively, to recency of purchase. When choice behavior is of the reinforcing type, the salience of recently purchased brands is high. This is consistent with the idea of an "enduring" set (Roberts and Lattin 1991). However, when choice behavior is of the variety-seeking type, recently purchased brands are less salient to consumers (McAlister 1982); under such conditions recency of purchase is negatively related to a brand's salience. These intertemporal preferences are different from preferences in the selection stage, because, for example, variety-seeking consumers may switch between colas and noncolas (intertemporal preferences) but may have more stable brand preferences within those two subsets (e.g., Coca Cola is generally preferred over Pepsi).

Third, Kamakura and Russell (1989, p. 385) show that consumers generally switch among brands in a certain price range. Accordingly, we propose that for every consumer, brands in one price range may be more salient than brands in others. Note that price ranges or tiers (e.g., Blattberg and Wisniewski 1989) are not based on shelf prices but constitute a more ordinal concept of price (i.e., high-priced, moderately priced, and low-priced brands), which reflects historical prices and long-term positioning strategies as opposed to current pricing tactics. Thus, ordinal or approximate memory representations of price in general suffice to determine choice set membership.

We expect a considerable amount of heterogeneity across consumers concerning the impact of each of these factors on choice set formation. With respect to the joint influence of these three factors, we assume that for a given consumer, brand salience must exceed a minimum threshold level at a specific choice occasion for that brand to be included in the choice set.

Brand selection. Choice or brand selection is assumed to be a true maximization of utility within the bounded set and is based on a compensatory trade-off of price and inherent preference (Bettman 1979; Gensch 1987; Wright and Barbour 1977). The latter concept of preference is static as opposed to the dynamic effects of the recency or intertemporal preference measure, as is illustrated previously. We refer to the combination of price and preference as *brand value.*

The Role of Shelf Price

The role of shelf price in our model is best illustrated by considering the consumer's reaction to an announced price promotion (e.g., by placing the brand on sale at the end of an aisle). Promotions of this type consist of a visual signal of the brand's availability and a monetary incentive to buy the brand (e.g., cents off). The end-of-aisle display makes the consumer aware of the physical availability of the brand. When noticed, it forces the consumer to consider the brand in the most literal sense of the word, because the consumer must decide to either evaluate the promoted brand for choice or ignore it and look for another brand. Hence, the placement and physical encounter triggers the consideration and not the discount. The discount enhances the subsequent attractiveness of the brand at the more in-depth evaluation stage of brand selection. Accordingly, the role of shelf prices is hypothesized to be confined to the brand selection stage. This hypothesis is corroborated by published evidence that shelf-prices are inspected infrequently (Dickson and Sawyer 1990; Hoyer 1984); hence, it seems a priori fallacious to assume full evaluation of prices at the choice set formation stage. More important, if consumers are not self-motivated to check prices, the rival hypothesis that price discounts affect choice set membership seems hard to substantiate. One implication of our hypotheses is thus that price discounts that are *unannounced* (i.e., brands are not placed at the end of the aisle or no shelf-talkers indicate the promotion) largely go unnoticed. Mitra and Lynch (1995, p. 646), noting that price discounts only become known to a consumer after the consumer considers a brand for choice, advocate a similar view.

The process that we hypothesize ensures a preselected set of brands in which the consumer may include brands that are highlighted in the store plus brands that were or were not purchased relatively recently (depending on either reinforcement or variety seeking tendencies) plus brands that are positioned in a preferred price range. It is evident that current shelf prices do not influence the construction of this set. As a consequence, there is no reason to expect consumers to engage in the mentally costly search, evaluation and comparison of current shelf prices of brands that are not in the choice set. Response to the prices of those brands should therefore be absent and those brands should thus be excluded from analyses of consumers' sensitivity to prices.

AN INDIVIDUAL-LEVEL TWO-STAGE CHOICE MODEL

Choice Set Formation

We assume that every consumer h has a specific latent threshold of salience Θ_t^h to consider a brand (i = [1 ... n]). Denote salience of brand i for consumer h at occasion t by S_{it}^h. From a modeler's perspective, salience S_{it}^h and the cutoff value Θ_t^h are observed indirectly with some error $\xi_{.t}^h$, or

$$S_{it}^h = s_{it}^h + \xi_{it}^h, i = [1,\dots,n]$$

and

$$\Theta_t^h = \theta_t^h + \xi_{n+1,t}^h.$$

We assume that the [n + 1] random components are iid draws from the Type I extreme value distribution. Note that the (n + 1)th random component is common across brands and makes so that Θ_t^h is a common threshold across brands for a given consumer at a given purchase occasion.

Similar to such studies as Andrews and Srinivasan's (1995), Han's (1993), and Roberts and Lattin's (1991), brand i is in the choice set of consumer h at purchase occasion t if $S_{it}^h > \Theta_t^h$. Under the distributional assumptions, the probability that consumer h includes brand i (i = 1,...,n) in choice set M at occasion t equals

$$(1) \qquad \pi(i \in M)_t^h = [1 + \exp(\theta_t^h - s_{it}^h)]^{-1}, i = [1,\dots,n].$$

As stated previously, we expect a considerable amount of heterogeneity across consumers in the probabilities $\pi(i \in M)_t^h$.

Brand Selection

Consumers compare the utilities V_{it}^h for brands that are in the choice set and choose the brand that maximizes utility. Hence, acknowledging that choice set membership of a brand is deterministic for the consumer and under the usual assumptions, that is, that $V_{it}^h = v_{it}^h + e_{it}^h$, and e_{it}^h are iid draws from the Type I extreme value distribution, the probability of choice is, after reduction of the universal set C, equal to

$$(2) \qquad P_{it}^h = \frac{I_{it}^h \cdot \exp(v_{it}^h)}{\sum_{\forall j} I_{jt}^h \cdot \exp(v_{jt}^h)},$$

$$\text{with } I_{it}^h = \begin{cases} 1 \text{ if i is in the choice set of consumer h at t.} \\ 0 \text{ if i is not in the choice set of consumer h at t.} \end{cases}$$

In contrast to the consumer, the modeler has imperfect knowledge about the indicators I_{it}^h. However, the modeler's knowledge about these indices is represented in the inclusion probabilities π_{it}^h. Given this probabilistic character of the actual choice set to the modeler, a reasonable maintained hypothesis of the choice probabilities is[1]

$$(3) \qquad P_{it}^h = \frac{\pi_{it}^h \cdot \exp(v_{it}^h)}{\sum_{\forall j \in C} \pi_{jt}^h \cdot \exp(v_{jt}^h)}$$

Note that it is only the relative magnitude of the inclusion probabilities that is relevant in Equation 3 and not the

[1]A justification of Equation 3 is available on request from the authors.

absolute magnitude. Multiplication of the π_{it}^{h}'s by a constant that is common across brands does not affect the choice probabilities.

Although both our model and that of Swait (1984) or Andrews and Srinivasan (1995) can be estimated within the confines of scanner data, because Swait's (1984) model enumerates all possible choice sets, the latter can be applied only to cases of small universal choice sets. If the universal set C has n brands, the numerator of the choice probability in Swait's (1984) study contains 2^{n-1} terms, and the denominator contains $2^n - 1$ terms. Equation 3 is not restrictive in this sense and remains estimable for any arbitrary size of the universal set.

OPERATIONALIZATION

Underlying the operationalization of our model is an attempt to divide explanatory variables into covariates of the deterministic part of the salience and the value of a brand i at occasion t for consumer h.[2] The deterministic part of the brand salience construct, s_{it}^{h} in Equation 1 is operationalized as a linear additive function of the following variables:

Promotion display. We define $Y_{1i}^{h}(t) = 1$ if the brand is displayed at the end of the aisle, and $Y_{1i}^{h}(t) = 0$ otherwise. This variable, among others, captures the visibility of the brand in the store which stimulates recall and recognition of the brand as a choice option.

Allocated shelf space. $Y_{2i}^{h}(t)$ measures the size (in meters) of the shelf space (facing) allocated to each brand. As with the previous variable, allocated shelf space increases the brand's salience to the consumer in the store.

Recency of choice. We define this term as $Y_{3i}^{h}(t) = (1 - \delta_{it}^{h}) \cdot \lambda^{rec} \cdot Y_{3i}^{h}(t-1) + \delta_{it}^{h}$, where δ_{it}^{h} is 1 if brand i was previously chosen by consumer h and λ^{rec} is a smoothing constant. This variable assumes the value 1.0 for the brand last chosen and exponentially slopes downward for other brands. Note that although "optically" similar, this measure differs from that of Guadagni and Little (1983), as discussed subsequently.

Preferred price-range membership. The dependence of brand salience on a preferred price range is operationalized as a set of dummies for price-range membership. Because price ranges are defined on average price, membership to a certain price range for a brand is time-invariant. If brand i belongs to range r, the salience function for brand i features an r-specific dummy that is shared by as many brands as there are in the price range. We define three price ranges. Hence, Y_{4i}, Y_{5i}, and Y_{6i} are 1 if the brand i is in range 1, 2, and 3, respectively, and 0 otherwise.

The deterministic part of the brand value construct, v_{it}^{h}, in Equation 3 is operationalized as a linear additive function of the following variables:

Inherent preference. We operationalize this measure in two parts. The first part is an overall preference measure, α_i, that consists of a set of brand constants; the second part, X_{1i}^{h} is a consumer-specific preference measure that is computed as the relative choice frequency over an initialization period of the data (Lattin and Bucklin 1989).

Unpromoted price: $X_{2i}^{h}(t)$ is defined as the regular price of the brand.

Price discount. $X_{3i}^{h}(t)$ measures a price discount in monetary terms. Price discounts are (arbitrarily) expressed as positive numbers, hence, the larger $X_{3i}^{h}(t)$, the deeper the price cut, and the lower the price actually paid.

Discussion

As is evident, we did not specify Guadagni and Little's (1983; hereafter G&L) loyalty measure as an explanatory variable because it combines what we refer to as *intertemporal preference* and *inherent preference*. Namely, the brand-by-brand geometric mean of the G&L loyalty measure over the choice history of a given consumer can be shown empirically to be either close or equal to the relative purchase frequencies in that choice history. Across consumers, it is therefore analogous to our X_{1i}^{h} preference measure in the brand value function. In addition, the G&L loyalty measure is increasing in the recency of choice, so longitudinally, it is analogous to our recency of choice measure in the salience function. Thus, both preference measures, recency of choice and inherent preference, are combined in the G&L loyalty measure, yet their idiosyncratic influence cannot be parceled out. The measurement we propose separates these components and thus provides a more detailed understanding of the function of the loyalty measure that has been critiqued for its ambiguous meaning elsewhere (Chintagunta, Jain, and Vilcassim 1991).

ESTIMATION

We estimate four model specifications: In the first model, the heterogeneous choice set formation model (HCSM), heterogeneity across consumers with respect to the choice-set-formation stage of the choice process is acknowledged to exist. Next, we estimate the case in which such heterogeneity is absent (CSM). The remaining model specifications are the latent class logit model (LCLM) by Kamakura and Russell (1989) and the G&L operationalization of the multinomial logit model (MNLM), which serve as benchmark models. Through their various operationalizations, all models account for consumer heterogeneity in brand preferences.

Data

We used regular powder detergent data from the Nielsen Scan 7000 system in France. In this category, variations on attributes such as scent and bleach are not present. There are 13 brands in this category, which makes it appealing for the study at hand because such a large universal set size makes it unreasonable to assume that all consumers search, evaluate, and compare all brand information and especially prices at all purchase occasions. In total, we have data for 1147 households who made at least 12 purchases in the category over a two-year period. To make estimation manageable, we sampled 169 households at random and obtained a total of N = 2979 observations for analysis. The remainder of the data set (978 households) was used for out-of-sample validation purposes. On average, sampled families made 17.62 purchases over the two-year period. The choice sequence of

[2]It may be possible that advertising raises both salience of a brand and its value. This would be the case when advertising helps to differentiate a brand (Mitra 1995), as well as to raise awareness for the brand. In such cases, advertising should be modeled in both stages of the choice process.

Table 1
DESCRIPTION OF THE ESTIMATION SAMPLE

Brand	*Availability*	*Price*	*Promotion*	*Shelf Space*	*Share*
		High-Price Range			
Skip	1.000	17.36	.09	3.02	.100
Ariel	1.000	17.10	.23	4.26	.174
Le Chat	.980	16.85	.04	1.42	.016
Persil	.885	16.55	.04	1.55	.064
Dash	1.000	16.36	.02	1.71	.089
Axion	1.000	16.33	.05	1.34	.106
		Medium-Price Range			
Supercroix	.977	15.16	.11	1.43	.051
Omo	1.000	14.97	.06	2.30	.134
		Low-Price Range			
Others	.960	13.91	.03	1.52	.018
X-tra	.980	13.54	.09	1.67	.084
Store Brand	.977	13.44	.05	2.22	.016
Bonux	.986	13.36	.07	1.49	.060
Gama	.842	13.35	.09	1.14	.089

each household was divided chronologically into three parts for initialization ($N_1 = 987$), estimation ($N_2 = 1005$), and validation ($N_3 = 987$). In Table 1, we describe the laundry detergent data set for 12 brands—plus a brand labeled "other"—in terms of availability, average price paid, average promotion intensity, average shelf space, and overall purchase share in the estimation sample. The table is organized in price tiers, which were obtained by maximizing the ratio of across- and within-tier price variance. Averages are taken over purchase occasions. Availability of the 13 brands is almost 100%. One attractive feature of our data worth noting is that shelf-space allocation measures are available for this category. These shelf-space measures are collected through store audits on a weekly basis and are measured in meters. No advertising exposure data were available for this category.

Estimation Procedure

Maximum likelihood estimation was done using a FORTRAN-based steepest gradient search with the Fletcher-Powell algorithm. We provide some estimation details per model specification. To facilitate the discussion, it is instructive to start with the CSM specification, though with respect to interpretation, we are more concerned with HCSM.

All parameters of CSM are statistically identified up to a metric for the brand constants in the choice stage and to a metric for the price-tier dummies in the choice set formation stage. Consequently, we set the corresponding parameters of one of the constants and one of the dummies to zero. The threshold of salience does not need to be operationalized but instead can be estimated latently. In the actual estimation of CSM, we used three sets of starting values for the parameter estimates: (1) the MNLM estimates, (2) zeros, and (3) twice the parameter estimates of earlier runs. In all three cases, the model converges to the same parameter estimates, though the step size of the algorithm had to be lowered in the last case. The value of the memory parameter of the recency variable was obtained from a grid search and equals $\lambda^{rec} = .79$.

To estimate the HCSM specification, we used a latent class approach and allowed the parameters in the function S^h_{it} and the threshold Θ^h_t to be distributed across households at the segment level. As a result, we are segmenting the market on structural differences between inclusion probabilities. In addition, because we investigate whether some households are more prone to respond to prices of brands in the choice set than others, we also estimated heterogeneity with respect to response to price and price-cut variables. The sample likelihood function for HCSM, including support points s = 1,...,S and associated probability masses, ψ_s, is equal to

$$(4) \qquad L = \prod_{h=1}^{H} \sum_{s=1}^{S} \psi_s \cdot \prod_{t=t_h}^{T_h} \frac{\pi^s_{it} \cdot \exp(v^s_{it})}{\sum_{j=1}^{n} \pi^s_{jt} \cdot \exp(v^s_{jt})}.$$

In this formulation, t_h and T_h mark the beginning and the end, respectively, of the choice history of a household, h (h = 1,...,H); s is a segment index (s = 1,...,S); i and j are brand indices; and π^s_{it} and v^s_{it} are as defined before with the household index h replaced by a segment index s. Finally, ψ_s is the relative size of segment s. To ensure that $0 \le \psi_s \le 1$, we reparametrized ψ_s as in Kamakura and Russell's (1989, p. 381) study. Akaike's information criterion suggests that for HCSM the underlying heterogeneity across households should be approximated by two segments. Kamakura and Russell's (1989) LCLM specification was estimated by initializing the estimation on the maximum likelihood parameters of MNLM. Akaike's criterion again suggested that two segments suffice to represent the heterogeneity across households underlying the estimation data for the LCLM specification.

Finally, the G&L MNLM specification was estimated along with the smoothing coefficient of the loyalty variable. Details of the approach used are provided in Fader, Lattin, and Little's (1992) study. The smoothing parameter was estimated at .65.

Model Fit

The estimation results, summarized in Table 2, indicate that HCSM provides a superior fit for the data used. Using Horowitz' (1983) test for nonnested hypotheses, HCSM fits better than both CSM and MNLM at the .001 level. Its adjusted $\bar{\rho}2$ is equal to .577, which is the highest of all model specifications. The test cannot be used to compare against LCLM, because the latter fits worse despite having more parameters. The CSM model fits better than MNLM and demonstrates a significant fit improvement over MNLM at the .001 level. Compared to LCLM, which has two segments, CSM fits better. The fit of Kamakura and Russell's (1989) model, LCLM, is significantly superior to MNLM at the .001 level. Finally, with an adjusted $\bar{\rho}^2$ of .558, the overall fit of MNLM is good; however, among all models considered, its fit is the poorest.

Interpretation of the Estimates.

We concentrate on the interpretation of the parameter estimates of HCSM and LCLM and comment on the differences of the implied segments. Other models considered can be interpreted as special cases of either HCSM or LCLM.

Two distinct segments underlie the sample according to the HCSM specification: The first ("in-store sensitive") segment consists of 36% of all households; the second ("loyal") segment consists of 64% of the households. The in-store sensitive segment shows a strong sensitivity to promotional signal and shelf space, coupled with a smaller—but still significant—estimate of the recency variable than that of the loyal segment (the difference between the estimates of recency across the two segments is significant at the .05 level). This lower dependence on the past suggests that the choice set for households in this segment is dynamic and follows the in-store environment. Response to the price-tier variables suggests that, other factors constant, brands in the moderate price range are salient to this segment. The simultaneous presence of multiple influences on brand membership of the choice set suggests that choice sets in this segment can, at specific occasions, be large. We show subsequently that the average choice set size in this segment equals 2.78 brands and that unit-size choice sets rarely occur. Price response over these implied choice sets is negative and significant.

Table 2
ESTIMATION RESULTS

	HCSM			*LCLM*		
	In-Store Sensitive Segment	*Loyal Segment*	*CSM*	*Segment1*	*Segment2*	*MNL*
BRAND VALUE						
Supercroix	0.000[a]		0.000[a]	0.000[a]	0.000[a]	0.000[a]
X-tra	.708		.687	2.148***	–.891***	–.624
Le Chat	.381		.064	.262	–7.800***	–.975**
Skip	1.029		.747	–.217	.168	–.158
Omo	.144		.122	2.001***	–.582*	.183
Persil	.804		.479	.785	–1.037***	–.421
Axion	1.494**		1.124**	.858	.168	.203
Gama	.999*		.936*	2.256***	–.709*	.062
Ariel	1.237*		.805	.631	–.080	.029
Bonux	.968*		.974*	–6.684***	–.585	–.200
Dash	1.460**		1.189**	1.027	–.087	.060
Private Label	.027		.010	.661	–2.183***	–1.167
Others	–.093		.006	.490	–1.858***	–1.576*
Preference	.989***		1.041***	—	—	—
Price	–.234***	.114	–.047	.426***	–.251***	–.016
Price cut	.653**	.306	.350	–.430	.545*	.320
BRAND SALIENCE						
Shelf Space	.230**	–.040	.067	.213***	.035	.076
Display	1.627***	.027	1.032***	.200	1.013***	.689***
Recency	3.225***	4.584***	4.087***	—	—	—
Low Range	0.000[a]	0.000[a]	0.000[a]	—	—	—
Medium Range	2.006***	.788	1.342***	—	—	—
High Range	.528	–.970	.129	—	—	—
THRESHOLD	4.287***	4.809***	4.632***	—	—	—
HETEROGENEITY						
Size constant	0.000[a]	.599	—	0.000[a]	.337	—
G&L LOGIT						
Loyalty	—	—	—	4.764***	4.707***	4.770***
LL^{begin}	–2543.4		–2543.4	–2543.4		–2543.4
LL^{end}	–1045.8		–1059.8	–1087.5		–1107.3
Akaike criterion	–1075.8		–1080.8	–1122.5		–1124.3
ρ^2	.589		.583	.572		.564
$\bar{\rho}^2$	.577		.575	.559		.558
number of parameters	30		21	35		17

*significant at .050 level.
**significant at .025 level.
***significant at .010 level (all one-sided).
[a]This constant is fixed at .000 to set a metric.

Table 3
PREDICTIVE VALIDATION RESULTS

	HCSM	*CSM*	*LCLM*	*MNL*
ρ^2	.591	.579[d]	.567[d]	.575[d]
LL^{end}	–668.382	–688.825[d]	–708.220[d]	–695.504[d]
RMSE[a]	.00952	.01531[d]	.00941	.00954
Hitrate	.68846	.67571[d]	.68236[d]	.68417[e]
ACP[b]	.57417	.55058[d]	.57237	.56424[d]
CoV[c]	1.73468	1.73764	1.62060[d]	1.60798[d]

[a]Root mean squared error of share predictions.
[b]Average Choice Probability (predicted).
[c]The ratio of ACP and the deviation in choice probabilities.
[d]Significantly different from HCSM at .05 level.
[e]Significantly different from HCSM at .10 level.

In the loyal segment, the single most important variable affecting choice set formation is recency of choice. Buying behavior of households in this segment appears to be habitual, and the consumers in this segment display no sensitivity to store environment variables. This exclusive reliance on recency of choice suggests that the distribution of inclusion probabilities is highly concentrated and, hence, that the implied choice sets are small for this segment. As is formally derived later, the implied choice set size in this segment is one brand for more that 60% of the choice occasions. Hence, many choices in this segment are choices by default, and it is thus not surprising that price response over the implied choice sets is nonexistent.

We briefly comment on the relatively low response to price ranges in our example. Contrary to our expectations, the response to the price-range dummies is not significant in three of four cases. We do not suggest a generalization of this finding across categories, however, and we will confine ourselves to the interpretation of our estimation results.

We note that LCLM has one segment that has a significant and positive price parameter. Moreover, LCLM and HCSM both estimate two segments—but these segments are different. Using Grover and Srinivasan's (1992) procedure to classify households to segments, we compared the shares of brands in the segments that LCLM and HCSM imply. The relative differences in shares, when contrasting the best matching configuration, ranges from 6% to 80% of the shares in the LCLM model (average = 45%). The absolute difference is 2.95 share points per brand, which suggests a structural difference in the identified segments.

Overall, the HCSM model is significantly superior in fit and implies different segments than LCLM. We agree that, substantively, the fit improvement of HCSM over LCLM is modest. Our next concern is to investigate the predictive performance of the alternative model specifications in holdout samples.

VALIDATION

Predictive Validation of the Models

In view of the marginal fit improvement of HCSM over LCLM, we investigate the predictions of the models and their distribution. To obtain the empirical distribution of predictive validation measures across multiple samples, we replicated the predictive validation for 25 independent holdout samples. These samples of approximately 1000 purchases were created by randomly drawing households from the parent sample of 978 households not used in estimation. Using the values of parameters reported in Table 2, we computed six accepted measures of predictive validity for each model: ρ^2, value of the log-likelihood, root mean squared error (RMSE) of the share predictions, hitrate, average choice probability, and the coefficient of variation (i.e., the ratio of the average choice probability over its deviation). To validate LCLM and HCSM, we assign households to segments using Kamakura and Russell's (1989) Bayesian procedure. In Table 3, the average validation statistics across the 25 samples are reported along with significance levels of the differences between HCSM and the three other models.

The results in Table 3 indicate that the predictive performance of HCSM is significantly better than all other models with respect to ρ^2, log-likelihood, hitrate, and average choice probability. The superiority of HCSM on the first two criteria indicates that the purchase sequences of households are most likely generated by HCSM. Kamakura and Russell's (1989) LCLM is best in predicting shares, but its predictions are not significantly better than HCSM. Note that MNLM outperforms the LCLM model in out-of-sample fit. This hints at the possibility that the LCLM model is overfitting the data in the estimation sample (e.g., Zenor and Srivastava 1993, p. 372). Finally, CSM performs the best on the coefficient of variation, with HCSM coming in second and the difference being nonsignificant. In addition, HCSM is superior to LCLM on this measure at the .001 level ($t = 17.30$). We conclude that HCSM is the best model specification in terms of fit and prediction on four criteria and that it shares honors on the remaining two.

Process Outcome Validation

Our estimation results suggest, along with Murthi and Srinivasan (1994), that response to short-term price variations seems to be absent for the loyal segment but seems to occur to some extent in the in-store sensitive segment. Beyond the scope of Murthi and Srinivasan's work (1994, p.11), however, we hypothesize that consumers respond to prices of only a subset of brands as opposed to prices of all brands. This section, in which we concentrate on the in-store sensitive segment, is included to substantiate this hypothesis further.

Using predicted inclusion probabilities from HCSM and a cutoff criterion on the probability that the brand is not in the choice set, we determine membership of the *complementary set*, that is, the universal set minus the restricted choice set. We next estimate a single stage (logit) choice model with two separate price effects, β_0 and β_1, conditional on the predicted membership of the complementary or choice set, respectively. We do this because direct estimation of β_0 and β_1 in a single stage gives a direct test of our model's capacity to differentiate meaningfully between brands that are in the choice set and those that are not. Hence, if a brand is predicted to be included in the choice set, the price parameter β_1 applies, otherwise the price parameter β_0 applies. The hypothesis of local price response holds that $\beta_0 = 0$ and $\beta_1 < 0$, that is, that price effects are only present when the brand is considered for choice.

In Table 4, we report β_0, β_1, and the log-likelihood for the estimated models for the in-store sensitive segment. Shelf prices are rescaled to a zero-mean to avoid a large illusory negative estimate of β_0 for any positive covariate (the brands on which β_0 is estimated should not be chosen). We use six alternative cutoff criteria, ranging from .95 to .90 and, for reference, a cutoff of 1.00 (global price response). A cutoff of .90 means that a brand is excluded from the choice set if our model predicts that the probability of the brand's exclusion is higher than .90. This will likely overestimate the actual choice set size, but that is of no consequence to the implication that response to prices outside the set should be 0. The specific values of the cutoff were chosen such that the joint probability of incorrectly rejecting a brand from the choice set was less than .5. This probability increases as the cutoff decreases and has an upper bound that is equal to the cutoff value raised to the power of the number of eliminated brands. To investigate whether our model's predictions of choice set membership hold outside the estimation sample, we replicated the analysis for the longitudinal holdout sample.

Table 4 accords well with our predictions both inside and outside the estimation sample. There is no price response to prices of brands that are predicted to be outside the choice set. The log of the likelihood ratio of the estimations under local price response and global price response is as high as 7.88 (cutoff = .94); that is, the likelihood of the sample under local price response is more than 2600 (= Exp[7.88]) times higher than that under global price response. This empirical analysis suggests that consumers respond to prices of only a limited brand set that is occasion- and household-specific, and hence the universal set does not appear to be the set over which households are price sensitive. Moreover, displayed and announced promotions typically makes a brand enter the choice set in the segment under analysis. The use of unannounced price discounts generally does not make a brand enter the choice set. Consistent with our assumptions and hypotheses, response to those price cuts is nonexistent in Table 4. Finally, the results support the idea that some consumers may search shelf prices for a small number of regularly purchased brands but that they are mainly passive information receivers for the remaining brands.

We conclude that our approach seems useful in identifying and predicting the sets over which consumers are price responsive and agree that more research is warranted on this subject.

SUBSTANTIVE RESULTS

In this section, we offer two final results implied by HCSM's estimates. First, we derive the distributions of the inferred choice set sizes for each of the two segments identified. Second, we take a brand perspective and contrast the measures of the structure of price competition that are implied by (1) the local price response as discussed previously and (2) the global price response that is implicit in a segment-specific logit model.

Inferring Choice Set Sizes of the Two Segments.

For each household and purchase occasion, we evaluated the distribution of the choice set size. We calculated the inclusion probabilities separately for households in both segments using HCSM. Subsequently, the individual probabilities π_{it}^h were rescaled to probabilities $\bar{\pi}_{it}^h$ to ensure that the highest probability was 1 (i.e., given a choice, the set cannot be empty). To calculate the probability of a choice set of size L, (L = 1,...,13), we compute the likelihood of all possible permutations of size L and sum their likelihoods per size. The likelihood of, for example, a choice set of size three and permutation C = {1, 2, 3} (assuming that brand 1 has the highest inclusion probability) is calculated as

$$(5)\quad P_t^h(1, 2, 3) = \bar{\pi}_{1t}^h \cdot \bar{\pi}_{2t}^h \cdot \bar{\pi}_{3t}^h \cdot \prod_{j=4}^{13} (1 - \bar{\pi}_{jt}^h), \bar{\pi}_{1t}^h = 1.0.$$

The implicit independence assumption in this equation (e.g., Hauser and Wernerfelt 1989) is in the probability domain and not in the domain of covariates. The covariates of π_{jt}^h may be, and are, correlated across brands (e.g., through recency). The independence assumption in probabilities expresses that we assume that no structural dependence between the inclusion probabilities is left unaccounted for. The average distribution of the choice set size in each segment is shown in Figure 1. The shapes of the two distributions across segments are strikingly different but intuitive.

The interpretation of the two distributions in Figure 1 is that the inferred size of the choice set in the loyal segment is 1 for 62% of the purchase occasions, 2 for 30%, 3 for 7%, and 4 for 1%. The average choice set size over all purchase occasions is 1.47. By consequence, the choice stage in the two-stage process involves in most cases a choice by default.

For the in-store sensitive segment, there are always "the other brand(s)." The size of the choice set is 1 for only 14% of the purchase occasions, whereas the expected choice set

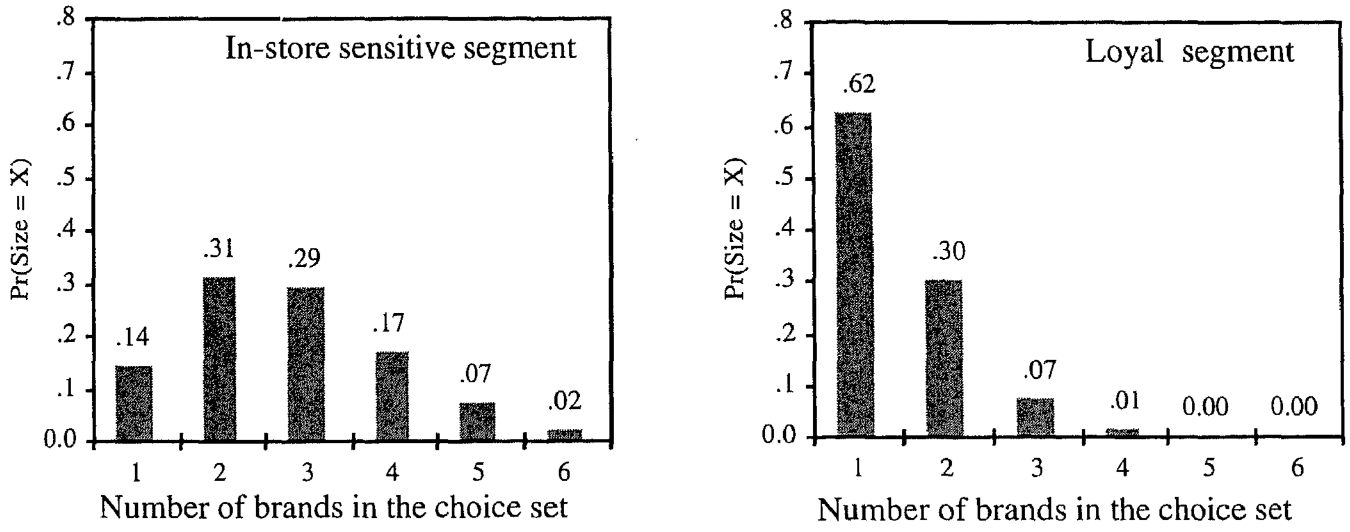
Table 4

PROCESS OUTCOME VALIDATION RESULTS

Cutoff[a]	β_1	β_0	*Eliminated Brands*[b]	*Log-Likelihood*
		Estimation Sample		
1.00[c]	–.253***	(–)	0.00	–594.12
.95	–.339***	–.028	4.84	–586.96
.94	–.357***	–.038	5.87	–586.24
.93	–.337***	–.033	6.52	–587.34
.92	–.310***	–.019	6.94	–588.99
.91	–.271***	–.005	7.24	–591.14
.90	–.191***	–.025	7.63	–595.26
		Hold-Out Sample		
1.00	–.225**	(–)	0.00	–482.35
.95	–.232***	.007	5.03	–480.37
.94	–.223***	–.016	6.02	–481.31
.93	–.191**	–.014	6.60	–482.52
.92	–.209**	–.034	7.04	–482.15
.91	–.170*	–.017	7.37	–483.24
.90	–.129*	–.007	7.63	–484.18

*significance (one sided) at .1 level.
**significance at the .05 level.
***significance at the .01 level.
[a]If the probability of rejection is larger than the value in column 1, then the brand is rejected from the choice set.
[b]The average number of brands that have a predicted probability of rejection from the choice set larger than the value in column 1.
[c]This case constitutes global price response.

Figure 1
THE DISTRIBUTION OF CONSIDERATION SET SIZE IN THE TWO SEGMENTS



size is equal to 2.78. Combined, the two distributions are in close agreement with Hoyer's (1984) observations of choice protocols at the supermarket shelf, which provides further face validity for our modeling approach.

Brand-Level Analysis

In this section, we analyze and evaluate measures of competitive clout and vulnerability. We show that *under global price response,* clout and vulnerability measures contain theoretically identical information and are simple transformations of market share. In contrast, *under local price response*, such measures are based on only those purchase occasions in which the brands of interest are truly in the choice set, which makes clout and vulnerability dependent on individual-level substitution patterns rather than market share alone. We prove this proposition, formulate its implications, and investigate the measures of competitive clout and vulnerability empirically.

Consider the logit cross elasticity η_{ij} of the change in aggregate choice probability (or market share) Pr_i for brand i in response to a price change in brand j (we drop the subscript t for expositional simplicity):

(6) $$\eta_{ij} = -Pr_j \cdot \beta_{price} \cdot Price_j, \forall i, j \in [1,...,n], i \neq j.$$

Assume, for the sake of exposition, that $\beta_{price} = -1$ and that prices of all brands are equal to 1. Then, using Kamakura and Russell's definition (1989, p. 386),

(7) $$Clout_i = \sum_{\forall j \neq i} (\eta_{ji})^2 = \sum_{\forall j \neq i} Pr_i^2 = (n - 1) \cdot Pr_i^2,$$

and

(8) $$Vulnerability_i = \sum_{\forall j \neq i} (\eta_{ij})^2 = \sum_{\forall j \neq i} Pr_j^2 = H - Pr_i^2,$$

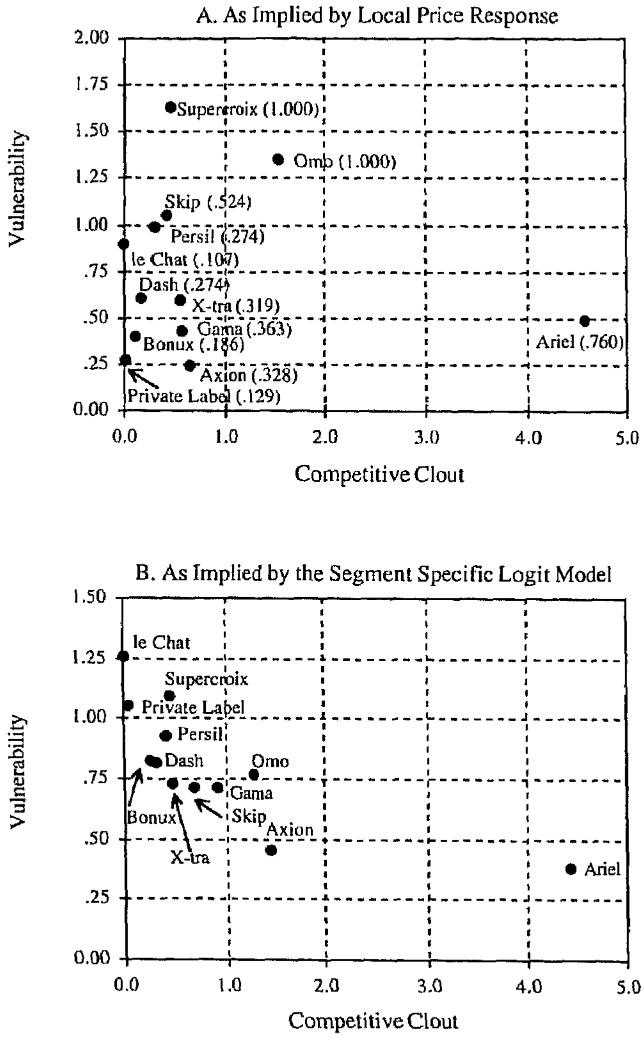
where H is the Herfindahl index. It follows that $Clout_i = (n - 1) \cdot (H - Vulnerability_i) = a - b \cdot Vulnerability_i$ and that clout and vulnerability are perfectly negatively related.[3] Relaxing the assumption of equal prices does not mathematically affect this identity. Moreover, under global price response, clout and vulnerability are uniquely driven by market share, up to variation in prices. Thus, a high-share brand has high clout and low vulnerability by definition. For low-share brands the opposite holds.

Another dependence holds for measures of clout and vulnerability under local price response; namely, if a brand cannot compete or be competed against if it is not in the choice set, both clout and vulnerability will be increasing in the frequency of choice set membership, all else being equal. Summarizing these relationships suggests that, under local price response, clout is positively related to both market share and choice set membership, whereas vulnerability is negatively related to market share but positively to choice set membership. Thus, accounting for the role of choice sets on price competition may effectively dispense of the identity between clout and vulnerability.

To investigate whether global price response indeed implies an identity of clout and vulnerability and whether, under local price response, these measures are contingent on choice set membership, we calculated price elasticities by increasing, one by one, a brand's price by 1%. An individual-level model was next used to compute the aggregated changes in choice share of any brand, and elasticities were calculated directly from these changes (for a similar approach, see, e.g., Bucklin, Gupta, and Siddarth 1994). Our subsequent analysis concentrates on the in-store sensitive segment, because there is no price response in the loyal segment. To compute the elasticities under local price response, we reduced the universal set of choice options for every specific choice occasion.

[3]We are indebted to the *JMR* reviewer who motivated us to pursue an explanation for the correlation in the bottom graph of Figure 2.

Figure 2
COMPETITIVE CLOUT AND VULNERABILITY[a]



[a]The figures in parentheses indicate the proportion of all purchase occasions in which the corresponding brand is predicted to be in the choice set. Due to differences in the denominator of the choice probabilities between local and global price response, the two graphs should not be compared in an absolute sense. Comparisons should be made relatively.

We disregarded only those brands that were predicted to be outside the set with a probability of .90 or higher. This seems justified because we observe from Table 4 that there is no response to prices in the complementary set.

In Figure 2, we present the 12 brands (the category "other" is not really a brand but a combination of small brands) in the clout-vulnerability plane. The top graph shows clout and vulnerability as estimated using local price response; the bottom graph shows the same measures as estimated using global price response. Under global price response, the correlation between clout and vulnerability is strongly negative, $r = -.75$ ($t = -3.8$). The graph produces a perfect ordering of (from left to right) low- to high-share brands, and the correlations between the segment-level market shares on the one hand and the square root of clout and vulnerability on the other are .98 ($t = 16.3$) and $-.89$ ($t = -7.1$), respectively. The hypothesis that the correlations are 1.0 and -1.0, respectively, cannot be rejected. This suggests that, under global price response, measures of clout and vulnerability do not add significant information to that contained in market shares (for a similar relation among clout and vulnerability, see Kamakura and Russell 1989, p. 385).

Under local price response, clout and vulnerability are uncorrelated for this data ($r = -.05$, $t = -.2$). Indeed, accounting for the existence of choice sets has the realistic implication that two brands may have equal competitive clout, yet one may be more vulnerable than the other. This would happen, for example, when one of the two brands is less effective in head-to-head competition between the two brands in isolation but competes effectively with a third brand. Although competitive clout is still related to market share, there is no direct relation between vulnerability and market share as was expected (the correlations as defined here are $r = .93$, $t = 8.4$ and $r = -.17$, $t = -.6$, respectively).

We conclude by highlighting the conditionality of clout and vulnerability on choice set membership. The top graph in Figure 2 shows that there are three brands that are frequently in the set: Supercroix, Omo, and Ariel. Exactly as expected, the top graph puts these three brands apart from the other brands and positions them as more pronounced in the competitive arena while cornering the other brands toward the origin of the clout and vulnerability plane. Consequently, by contrasting the two graphs, it seems that the competitive clout of Axion is overestimated by global price response because it incorrectly assumes that Axion is always in the choice set. Likewise, though global price response suggests that the Store Brand is vulnerable, it appears from our analysis that its position is much stronger once we restrict the analysis to the occasions that the Store Brand is actually considered for choice.

CONCLUSIONS

Dickson and Sawyer (1990) concluded that research on price should start accounting for the effects that displays, shelf-talkers, and shelf-space allocations have on price response behavior. We have attempted to address some of their concerns. Rather than venturing that all consumers respond to prices of all brands at all purchase occasions, we have attempted to model the limited set over which a consumer is price responsive. Important determinants of this set are exactly the same measures that Dickson and Sawyer asked to be included in price research. More generally, our results indicate that price responsiveness is closely linked with differences in salience across brands.

The existence of choice sets implies an intricate set of interactions between salience- and value-generating variables. Thus, when both types of variables are included in a simple one-stage model, utility functions of such models are a priori misspecified. Indeed, there is no compelling reason why larger shelf-space allocations would raise the utility of a brand. Likewise, there is no strong argument to be made that recency of purchase is a cause for utility for any given brand; recency of purchase merely covaries with utility across brands provided that consumers buy brands they prefer. Both of these measures are, however, credible causes of brand salience at the point of purchase. Their role on choice is by consequence only indirect and dictates the extent of evaluation of value-generating variables such as price and price discounts.

It seems from our empirical study that the implied assumption of simple one-stage choice models—that consumers evaluate all brands for choice—is not always correct. Our suggested approach serves to relax this assumption. In conclusion, managerially, to understand competitive dynamics at the brand level, a person should deal with the implications of observed scarcity of consumer search for information (e.g., Dickson and Sawyer 1990; Hoyer 1984) and should focus on those brands that are frequently in the choice set. Hence, it is important to have models or approaches, like the one we discuss, that can identify those brands from readily available scanner purchase files.

REFERENCES

Alba, Joseph W., J. Wesley Hutchinson, and John G. Lynch (1991), "Memory and Decision Making," in *Handbook of Consumer Behavior*, T. S. Robertson and H. H. Kassarjian, eds. Englewood Cliffs, NJ: Prentice Hall.

Andrews, Rick L. and T. C. Srinivasan (1995), "Studying Consideration Effects in Empirical Choice Models Using Scanner Panel Data," *Journal of Marketing Research*, 32 (February), 30–41.

Bettman, James (1979), *An Information Processing Theory of Consumer Choice*. Reading, MA, Addison-Wesley.

Blattberg, Robert C. and Kenneth J. Wisniewski (1989), "Price-Induced Patterns of Competition," *Marketing Science*, 8 (4), 291–309.

Bucklin, Randolph E., Sunil Gupta, and S. Siddarth (1994), "Determining Segmentation in Sales Response Across Consumer Purchase Behaviors," working paper, Anderson Graduate School of Management, University of California, Los Angeles.

Chintagunta, Pradeep K., Dipak C. Jain, and Naufel J. Vilcassim (1991), "Investigating Heterogeneity in Brand Preferences in Logit Models for Panel Data," *Journal of Marketing Research*, 28 (November), 417–28.

Dickson, Peter R. and Alan G. Sawyer (1986), "Point-of-Purchase Behavior and Price Perceptions of Supermarket Shoppers," working paper, Cambridge, MA: Marketing Science Institute.

——— and ——— (1990), "The Price Knowledge and Search of Supermarket Shoppers," *Journal of Marketing*, 54 (July), 42–53.

Fader, Peter S., James M. Lattin, and John D.C. Little (1992), "Estimating Nonlinear Parameters in the Multinomial Logit Model," *Marketing Science*, 11 (4), 327–47.

Fazio, Russell H., Martha C. Powell, and Carol J. Williams (1989), "The Role of Attitude Accessibility in the Attitude to Behavior Process," *Journal of Consumer Research*, 16 (December), 280–88.

Gensch, Dennis (1987), "A Two-Stage Disaggregate Attribute Choice Model," *Marketing Science*, 6 (Summer), 223–31.

Grover, Rajiv, and V. Srinivasan (1992), "Evaluating the Multiple Effects of Retail Promotions on Brand Loyal and Brand Switching Segments," *Journal of Marketing Research*, 29 (February), 76–89.

Guadagni, Peter M. and John D. C. Little (1983), "A Logit Model of Brand Choice Calibrated on Scanner Data," *Marketing Science*, 2 (Summer), 203–38.

Han, Sangman (1993), "A Threshold Model of Consideration Set Formation," doctoral thesis, Columbia University.

Hauser, John R. and Birger Wernerfelt (1989), "The Competitive Implications of Relevant Set/Response Analysis," *Journal of Marketing Research*, 26 (November), 391–405.

——— and ——— (1990), "An Evaluation Cost Model of Consideration Sets," *Journal of Consumer Research*, 16 (March), 393–408.

Horowitz, Joel L. (1983), "Statistical Comparison of Non-Nested Probabilistic Discrete Choice Models," *Transportation Science*, 17 (August), 319–50.

Hoyer, Wayne D. (1984), "An Examination of Consumer Decision Making for a Common Repeat Purchase Product," *Journal of Consumer Research*, 11 (December), 822–29.

Kamakura, Wagner A. and Gary J. Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research*, 26 (November), 379–90.

Kardes, Frank, Gurumurthy Kalyanaram, Murali Chandrashekaran, and Ronald J. Dornoff (1993), "Brand Retrieval, Consideration Set Composition, Consumer Choice, and the Pioneering Advantage," *Journal of Consumer Research*, 20 (June), 62–75.

Lattin, James M. and Randolph E. Bucklin (1989), "Reference Effects of Price and Promotion on Brand Choice Behavior," *Journal of Marketing Research*, 26 (August), 299–310.

Lehmann, Donald R. and Yigang Pan (1994), "Context Effects, New Brand Entry and Consideration Sets," *Journal of Marketing Research*, 31 (August), 364–74.

McAlister, Leigh (1982), "A Dynamic Attribute Satiation Model of Variety-Seeking Behavior," *Journal of Consumer Research*, 9 (September), 141–50

Meyer, Robert J. and T. C. Eagle (1982), "Context-Induced Parameter Instability in a Disaggregate Stochastic Model of Store Choice," *Journal of Marketing Research*, 19 (February), 62–71.

Mitra, Anusree (1995), "Advertising and the Stability of Consideration Sets Over Multiple Purchase Occasions," *International Journal of Research in Marketing*, 12 (1), 39–54.

——— and John G. Lynch (1995), "Toward a Reconciliation of Market Power and Information Theories of Advertising Effects on Price Elasticity," *Journal of Consumer Research*, 21 (4), 644–60.

Murthi, B. P. S. and Kannan Srinivasan (1994), "A Study of Consumers' Extent of Evaluation in Brand Choice Decision: A Multi-State Evaluation Choice Model," working paper, University of Texas, Dallas.

Nedungadi, Prakash (1990), "Recall and Consumer Consideration Sets: Influencing Choice Without Altering Brand Evaluation," *Journal of Consumer Research*, 17 (December), 263–76.

Roberts, John H. and James M. Lattin (1991), "Development and Testing of a Model of Consideration Set Composition," *Journal of Marketing Research*, 28 (November), 429–40.

Shocker, Allan D., Moshe Ben-Akiva, Bruno Boccara, and Prakash Nedungadi (1991), "Consideration Set Influences on Consumer Decision-Making and Choice: Issues, Models and Suggestions," *Marketing Letters*, 2 (3), 181–97.

Siddarth, S., Randolph E. Bucklin, and Donald G. Morrison (1995), "Making the Cut: Modeling and Analyzing Choice Set Restriction in Scanner Panel Data," *Journal of Marketing Research*, 32 (August), 255–66.

Swait, Joffre D. (1984), "Probabilistic Choice Set Generation in Transportation Demand Models," doctoral dissertation, Department of Civil Engineering, Massachusetts Institute of Technology.

Urban, Glenn L., John S. Hulland, and Bruce D. Weinberg (1993), "Premarket Forecasting for New Consumer Durable Goods: Modeling Categorization, Elimination and Consideration Phenomena," *Journal of Marketing*, 57 (April), 47–63.

Wright, Peter and Frederick Barbour (1977), "Phased Decision Strategies: Sequels to Initial Screening," in *Multiple Criteria Decision Making*, Martin Starr and Milan Zeleny, eds. Amsterdam: North Holland TIMS Studies in Management Science.

Zenor, Michael J. and Rajendra K. Srivastava (1993), "Inferring Latent Structure with Aggregate Data: A Latent Segment Logit Approach," *Journal of Marketing Research*, 30 (August), 369–70.