

The authors present a model that maps competitive market structures by identifying the preference structure of each consumer segment. By marrying two different data types—switching probabilities and attribute ratings—their model divides a market into several homogeneous submarkets in which consumers consider a distinctive subset of brands (consideration set or competitive group) with a segment-specific rule for attribute evaluations and a segment-specific ideal point. Using data published in Harshman and colleagues' (1982) work, the authors examine the U. S. car market and find brand-loyal segments for all car types except those favored by first-time buyers, a universal market, and five switching segments that consider car groups differing in the nation of origin, size, and luxury level. Breaking the switching segment into finer partitions gives a better account of the data than the Colombo-Morrison model or an asymmetric generalization of that model. The authors advocate the development of marketing goals with respect to each of the segment maps in the hope that it will lead to more synergistic marketing strategies for brands encountering multifaceted competition.

## Building Market Structures From Consumer Preferences

Products in a market compete with widely differing intensities. Nobody believes, for example, that the Lexus LS400 competes more intensely with the Dodge Neon than with the Cadillac STS and the Infinity Q45. The identification of competitive groups is one of the major purposes of competitive market-structure (CMS) analysis. Trade-in data or switching probabilities have long been used to identify competitive groups (cf. Kalwani and Morrison 1977).

When considering options within a competitive group, consumers may well have segment-specific evaluative criteria. A consumer, who considers the Lexus LS400, the Cadillac STS, and the Infinity Q45 may weigh underlying product attributes such as comfort or prestige, but neglect those such as economy. Another consumer, however, who considers the Nissan Sentra, the Ford Tempo, and the Dodge Neon may evaluate product attributes such as economy rather than those of prestige or sportiness. Attribute ratings or the factors underlying attribute ratings are the typical data used to identify evaluative frames of reference.

Each of these two data types—switching probabilities and attribute ratings—is crucial for understanding different

aspects of market structure. The marketing literature, however, has never put them together to form an overall picture of how market structure is built. We present a model that does just that and, as a by-product of marrying these two data types, provide five key insights into market structure. First, we obtain a segment-by-segment account of the differences in consideration sets or competitive groups. Some people may consider all brands, but many consumer segments focus on subsets more narrowly aligned with segment needs or expectations. Second, we obtain a segment-by-segment account of the differences in evaluative criteria. Third, we obtain maps of market structure. Fourth, we obtain different ideal points for each segment. Fifth, we obtain a segment-by-segment account of which brands are gaining and which are waning—a longitudinal dynamic. An overall stable market share in every segment means something different than a share that is growing in some segments and shrinking in others. If Lexus were losing share with respect to Cadillac, but gaining an equivalent amount with respect to less luxurious imports, the stable share might be viewed as a substantial failure. No other method or model combines all of these features.

The remainder of this article is organized as follows: In the first section, we review the previous research on competitive market structure and consumer preference structure. In the second section, we develop the model by presenting the basic behavioral principles and, then, the mathematical assumptions and their formulation. In the third section, we show the estimation of the parameters and the statistical test of the competitive market structure. In the fourth section, we

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present the results of the application of the model to the car trade-in data from Harshman and colleagues' (1982) study. Finally, in the fifth section, we mention some further extensions of the model.

#### REVIEW: MARKET STRUCTURE ANALYSIS AND PREFERENCE STRUCTURE ANALYSIS

Four major schemes have been used for classifying approaches to market structure analysis. Day, Shocker, and Srivastava (1979) categorize the CMS methods on the basis of the types of data used: behavioral or judgmental data. Bourgeois, Haines, and Sommers (1987) create two-by-two classifications that cross supply- or demand-oriented measures with behavioral or judgmental measures. Shocker, Stewart, and Zahorik (1990) cross behavioral versus judgmental measures with the testing versus determining function. They also differentiate another aspect of the classification: spatial versus nonspatial representation of competitive market structures. Deshpandé and Gatignon (1994) discuss three different approaches: those based on the analysis of actual purchases made by consumers, the analysis of consumer judgments, and the inferences made from the strategies exhibited by the competitors. Thus, CMS models vary in terms of the measures analyzed, the function transforming measures to distances, and the mapping of distances into clusters, trees, or spatial representations.

Regardless of the differences in CMS models, they share some objectives in common. One prime objective is to diagnose the status of competition. Toward this end, we believe five elements must be emphasized. The first element is the *identification of competitive groups*.<sup>1</sup> There is structure to a market. This is almost a basic postulate. Brands are not uniformly distributed throughout some competitive space. Competition between brands is neither uniform nor simply proportional to market shares. That is, brands can be represented in groups—with intense rivalry within a group and lessened rivalry between groups. Some CMS models deal with this issue by subgrouping<sup>2</sup> brands either a priori (Bucklin and Srivastava 1991; Grover and Dillon 1985; Inoue 1993; Kalwani and Morrison 1977; Kannan and Wright 1991; Kumar and Sashi 1989; McCarthy et al. 1992; Novak 1993; Novak and Stangor 1987; Urban, Johnson, and Hauser 1984) or posteriori (Grover and Srivastava 1987; Jain, Bass, and Chen 1990; Ramaswamy and DeSarbo 1990; Rao and Sabavala 1981).

The second common element concerns the representation of the *heterogeneity of consumer preferences*. Some models represent heterogeneity by allowing scaling parameters of brand utility or attribute importances to differ across households and usage situations (Bucklin and Srivastava 1991; DeSarbo and Cron 1988; Dillon, Kumar, and de Borrero 1993; Kamakura and Russell 1989; Russell, Bucklin, and

Srinivasan 1993; Zenor and Srivastava 1993). Other models incorporate heterogeneous choice-probability distributions across (several types of) consumers (Colombo and Morrison 1989; Grover and Dillon 1985; Grover and Srivastava 1987; Inoue 1993; Jain, Bass, and Chen 1990; Kalwani and Morrison 1977; McCarthy et al. 1992; Novak 1993; Novak and Stangor 1987; Urban, Johnson, and Hauser 1984).

The third element is the manner in which *preference is composed*. The principal way is to associate brand attributes, such as price or sportiness, with total utilities (Bucklin and Srivastava 1991; DeSarbo and DeSoete 1984; DeSarbo and Rao 1986; Dillon, Kumar, and de Borrero 1993; Hauser and Shugan 1983; Kamakura and Russell 1989; Kannan and Wright 1991; Russell 1992; Russell and Bolton 1988; Russell, Bucklin, and Srivastava 1993; Shugan 1987; Zenor and Srivastava 1993).

The fourth element is *asymmetry in competition*. For example, the extent to which Brand A affects Brand B is not necessarily the same as the extent to which Brand B affects Brand A. One approach to asymmetry involves the explicit specification of the asymmetry in models (Cooper 1988; DeSarbo and Manrai 1992; Harshman et al. 1982; Ramaswamy and DeSarbo 1990; Russell 1992). Another approach uses the *posteriori* estimation or calculation of asymmetric indices such as clout or vulnerability (Bucklin and Srivastava 1991; Kamakura and Russell 1989).

The fifth and last element is the *pictorial representation* of competitive market structures. Scrutinizing tables of parameter estimates is a laborious task for managers—even for academicians. On the other hand, a pictorial representation can be an easy-to-comprehend and interpretively rich representation of competitive market structures. We have two types of models that represent competitive market structures either spatially (maps) (e.g., Cooper 1988; DeSarbo and Manrai 1992; DeSarbo and Rao 1986; Elrod 1988; Hauser and Shugan 1983; Katahira 1990; Shugan 1987) or ultrametrically<sup>3</sup> (trees) (e.g., Grover and Dillon 1985; Kalwani and Morrison 1977; Novak 1993; Ramaswamy and DeSarbo 1990; Rao and Sabavala 1981; for a review of latent structure mapping methods, see DeSarbo, Manrai, and Manrai 1994; and for a review of latent structure nonspatial models, see DeSarbo, Manrai, and Manrai 1993).

The previous discussion is summarized in Table 1. Note, there is no CMS analysis model that takes into consideration all five elements. Therefore, the contribution of the model we present is that it captures all five elements: competitive groups, heterogeneity of consumer preferences, the evaluative schemata of each segment, the asymmetry inherent in consumer preferences over time, and pictorial representations. It builds a representation of competitive market structure from its foundations in the preference structure of each segment.

<sup>1</sup>The idea of the identification of competitive groups is limited to the cases in which distinctive membership of brands to groups is derived. Grover and Srivastava's (1987) latent-class analysis of the coffee market does this, whereas Cooper's (1988) competitive map of the coffee market does not identify competitive groups.

<sup>2</sup>Subgrouping in our definition must divide brands into groups that are different from the others. Thus, we do not consider, as a grouping model, a model that only reveals the degree or probability of membership to groups in which all brands are included or ones in which differences are reflected only in external measures such as attribute weights (e.g., Dillon, Kumar, and de Borrero 1993) or dimensionality (e.g., DeSarbo and Rao 1986).

<sup>3</sup>We do not consider models or methods as providing a picture if they merely divide a market into subgroups because the function of this kind of model is just a partition (e.g., Grover and Srivastava 1987), if they merely represent competitive market structures pictorially on the basis of the plot of parameters (e.g., Kamakura and Russell 1989), or if they can be represented spatially or ultrametrically but do not explicitly consider the distance between brands (e.g., Kannan and Wright 1991).

Table 1  
REVIEW: MARKET STRUCTURE ANALYSIS AND PREFERENCE STRUCTURE ANALYSIS

	Competitive Groups	Heterogeneous Consumers	Preference	Asymmetry	Pictorial Representation
Bucklin and Srinivasan (1991)	A	S	YES	$P_t$	
Chintagunta (1994)	$P_i$	S	YES		MAP
Colombo and Morrison (1989)		$P_d$			
Cooper (1988)				M	MAP
DeSarbo and De Soete (1984)	$P_i$			M	TREE
DeSarbo and Rao (1986)			YES		MAP
DeSarbo and Manrai (1992)				M	MAP
Dillon, Kumar, and de Borrero (1993)		S	YES		
Elrod (1988)					MAP
Grover and Dillon (1985)	A	$P_d$			TREE
Grover and Srinivasan (1987)	$P_i$	$P_d$			
Jain, Bass, and Chen (1990)	$P_i$	$P_d$			
Harshman and colleagues (1982)				M	
Hauser and Shugan (1983)			YES		MAP
Inoue (1993)	A	$P_d$			
Kalwani and Morrison (1977)	A	$P_d$			TREE
Kamakura and Russell (1989)		S	YES	$P_t$	
Kannan and Wright (1991)	A		YES		
Katahira (1990)					MAP
Kumar and Sashi (1989)	A				
McCarthy and colleagues (1992)	A	$P_d$			
Novak (1993)	A	$P_d$			TREE
Ramaswamy and DeSarbo (1990)	$P_i$		YES	M	TREE
Rao and Sabavala (1981)	$P_i$				TREE
Russell and Bolton (1988)			YES		
Russell (1992)			YES	M	
Russell, Bucklin, and Srinivasan (1993)		S	YES		
Russell and Kamakura (1994)		S	YES	M	MAP
Shugan (1987)			YES		MAP
Urban, Johnson, and Hauser (1984)	A	$P_d$			
Zenor and Srivastava (1993)		S	YES		

Note:

- A = a priori identification.
- $P_i$  = posteriori identification.
- S = different scaling of parameters.
- $P_d$  = different choice-probabilities.
- $P_t$  = posteriori treatment.
- M = modeling.

MODELING: ASSUMPTIONS AND FORMULATION

Preliminary Behavioral Principles

We begin with four basic principles concerning consumers' decision-making process and associate them with the notion of the competitive groups.

1. Consumers evaluate brands on the basis of their underlying *attribute values*. Their *evaluation schemata* (the composite of the attributes and importances) differ across consumers. We assume a multiattribute attitude model (i.e., a linear compensatory model) (cf. Bettman 1979) with heterogeneous importance weights on attributes in consumers' evaluation rules. In other words, consumers evaluate a car on the basis of attributes such as sportiness or comfort. The relative importance of these attributes differs across consumers.
2. Consumers have different *ideal profiles* of brand (i.e., ideal points). We assume the ideal-point model (Carroll 1972; Carroll and Chang 1967; Coombs 1964) in which product attributes are not valued monotonically (i.e., not on a more-is-better basis), but on the basis of the proximity to their ideal level or point. For example, consumers might prefer a car with 130 horsepower to one with 300 horsepower because the former is easier to maneuver; but, on the other hand, a 130-horsepower car might be preferred to a 50-horsepower car because the latter might be perceived as impractical for accel-

erating onto expressways. Hence, ideal points exist with respect to horsepower. We assume that these ideal points vary across consumers.

3. Consumers have different *consideration sets* of brands. Consideration sets are homogeneous within segments and heterogeneous across segments. For example, a consumer seeking comfort and prestige in a car might consider the Lexus LS400, the Cadillac STS, and the Infinity Q45, but not the Hyundai Excel or the Toyota Corolla. Another consumer, considering cars just as the methods of transportation, might consider the Excel and the Corolla instead of the LS400 or the STS.
4. We can divide a market into a certain number of *submarkets* in which *homogeneous* consumers consider a distinctive subset of brands with a particular rule of attribute evaluation and reference to a specific ideal point. Thus, we deal with the heterogeneity of consumers in terms of consideration sets or choice sets, attribute-evaluation schemata, and ideal points and assume that, with respect to these terms, consumers are homogeneous within segments and heterogeneous across segments.

These four principles are the building blocks of competitive market structure. In summary, we seek to portray a competitive market as a series of heterogeneous competitive

groups that have homogeneous consideration sets and preference structures (ideal points and attribute evaluation) within groups. We next translate these behavioral principles into mathematical and statistical assumptions.

*Assumption 1: Ideal Points and Preference Structure*

Brand  $i$ 's ( $i = 1, \dots, I$ ) attraction in submarket  $k$  ( $k = 1, \dots, K$ ),  $\alpha_{ik}$ , is specified as follows:

$$(1) \quad \alpha_{ik} = -\log \delta_{ik} + \epsilon_{ik}.$$

The translation of distance into attraction is similar in Katahira's (1990) study. In Equation 1,  $\delta_{ik}$ , a distance of brand  $i$  from an ideal point in submarket  $k$ , is calculated from

$$(2) \quad \delta_{ik} = \sqrt{\sum_{d=1}^{D_k} (x_{idk} - x_{dk}^*)^2},$$

where  $x_{idk}$  is the  $d$ th coordinate of brand  $i$  in submarket  $k$ , and  $x_{dk}^*$  is the  $d$ th coordinate of an ideal point in  $D_k$ -dimensional space in submarket  $k$ .

The vector model can be thought of as a special case of the ideal-point model in which the ideal point is substantially outside the envelope of brand configurations. Hence, if we get a large enough value of an ideal-point estimate, the preference model can be interpreted as the vector model in which the preference monotonically increases as attribute values change in the preferred direction.

*Assumption 2: Brand Positions*

Because each segment can value the underlying attributes differently, we represent a brand's position in the map for each segment as a linear combination of the value of that brand on the underlying attribute times the importance of that attribute in this particular segment. The coordinate of brand  $i$  in submarket  $k$  on  $d$ th dimension,  $x_{idk}$ , is

$$(3) \quad x_{idk} = \sum_{a=1}^A Z_{ia} \beta_{adk},$$

where  $Z_{ia}$  is the value of underlying attribute  $a$  ( $a = 1, \dots, A$ ) of brand  $i$ , and  $\beta_{adk}$  is the importance of attribute  $a$  with respect to the  $d$ th dimension in submarket  $k$ .<sup>4</sup>

Without restrictions on the origin and unit of measure for the brand coordinates and the ideal points, the solution would be unidentified. Therefore, we have added the following restrictions:

<sup>4</sup>Note that this frees each segment map to have a number of dimensions that is perhaps uniquely relevant to that particular segment, rather than constrains all maps to have the dimensionality of the underlying attributes. This flexibility is especially desirable when we study consumer markets that can differ substantially in what each considers to be important. Reparameterizing brand coordinates in terms of brand attributes has long been employed in marketing applications of multidimensional scaling (cf. DeSarbo, 1982).

$$(4a) \quad \sum_{i \in S_k} x_{idk}^2 + x_{dk}^{*2} = 1,$$

$$(4b) \quad \sum_{i \in S_k} Z_{ia} = 0,$$

and

$$(4c) \quad \sum_{i \in S_k} Z_{ia}^2 = 1.$$

Equation 4a confines the size of the entire configuration, including both brand coordinates and an ideal point within submarkets. Equations 4b and 4c normalize the attribute values within submarkets and, in turn, center the brand configuration.<sup>5</sup>

The specification of brand coordinates based on attribute values, as equations 2 and 3 indicate, is an external analysis-of-preference model (cf. DeSarbo and Carroll 1985; DeSarbo and Rao 1986), because it develops the brand positions by reparameterizing the attribute data and maps the ideal points into that space using the switching probabilities.

*Assumption 3: Competitive Market Structure*

A market (a group of heterogeneous consumers seeking to satisfy common needs) is categorized into  $K$  submarkets (subgroups of homogeneous consumers),  $S_k$  ( $k = 0, \dots, K$ ), with the relative size denoted by  $w_k$  ( $k = 0, \dots, K$ ), where  $\sum_{k=0}^K w_k = 1$ . Each submarket has its own consideration set or choice set, its own rule of attribute evaluation, and an ideal point, all of which differ across submarkets.

We define  $S_0$  as a *universal* market in which all brands offered are considered. We allow for a universal market for two reasons. First, there undoubtedly is a common theme that ties these brands together into a single market. Although markets can evolve far from the original common need that underlies their initial formation, studying the evaluation scheme that at least loosely ties all brands together can be helpful in brand planning. Second, we can use the universal market to construct a null market-structure hypothesis,  $H_0$ , where  $w_0 = 1$ . That is, the market has not evolved past this unstructured or unpartitioned phase. Under this null structure, all brands in the market compete with each other equally (i.e., proportionally to their market shares). In an unstructured market, brand-choice probabilities are specified by the aggregate constant-ratio model (cf. Urban, Johnson, and Hauser 1984).

By choosing different specifications of the segments,  $S_k$  ( $k = 1, \dots, K$ ), we can represent market structures composed of hard-core loyal buyers and potential-switcher submarkets (Colombo and Morrison 1989) or brand-loyal and switching submarkets (Grover and Srinivasan 1987). An  $S_k$  that contains only one brand represents the hard-core loyal or brand-loyal submarket, and an  $S_k$  that contains more than one brand is the potential-switcher or switching submarket.

<sup>5</sup>These constraints are not sufficient to identify the vector preference model. As was indicated previously, the vector model is interpreted empirically when the ideal point lies outside the envelope of brands in a map. For the general ideal-point model, these constraints are sufficient for identification up to a rigid rotation of axes.

*Assumption 4: The Distribution of Errors*

The error,  $\epsilon_{ik}$  in Equation 1 is independently and identically distributed as an extreme-value distribution type I. Consequently, the probability,  $p_{ik}$ , that brand  $i$  is chosen in submarket  $k$  is (cf. McFadden 1974)

$$(5) \quad p_{ik} = \frac{\exp(-\log \delta_{ik})}{\sum_{j \in S_k} \exp(-\log \delta_{jk})} = \frac{\delta_{ik}^{-1}}{\sum_{j \in S_k} \delta_{jk}^{-1}}$$

In Equation 5, we assume that the probability is a function of attractions within each submarket and is analogous to the multiplicative competitive interaction model (cf. Cooper and Nakanishi 1988) that associates attractions with market shares.

*Assumption 5: Asymmetric Stochastic Choice Process and Momenta*

The joint probability,  $p_{ijk}$ , that in submarket  $k$  brand  $i$  is chosen at time  $t$  and brand  $j$  is chosen at time  $t + 1$  ( $i, j \in k$ ) is specified on the basis of the quasi-zero-order stochastic-choice-process assumption as follows:

$$(6) \quad p_{ijk} = p_{ik} p_{jk}^{(M)} = p_{ik} M_{jk} p_{jk}$$

That is, the choice probability of brand  $j$  in submarket  $k$  at time  $t + 1$  is augmented by a process-dynamics parameter we call *momentum*,  $M_{jk}$ . At market level, the joint probability,  $p_{ij}$ , that brand  $i$  is chosen at time  $t$  and brand  $j$  is chosen at time  $t + 1$  is specified in the following way:

$$(7) \quad p_{ij} = \sum_{k=1}^K p_{ijk} w_k = \sum_{k=1}^K p_{ik} M_{jk} p_{jk} w_k$$

To understand the use of the term *momentum*, first note that one popular way to obtain symmetric probabilities from asymmetric switching probabilities is to replace the element  $p_{ij}$  with the average,  $(p_{ij} + p_{ji})/2$  (cf. Rao and Sabavala 1981). The difference between this and the asymmetric representation is  $(p_{ij} - p_{ji})/2$ . Because  $p_{ij}$  can be thought of as proportional to the rate of change of  $i$  into  $j$ , the difference can be thought of as the analog of a resultant velocity (i.e., how fast  $j$  transitions to  $i$  relative to how fast  $i$  transitions to  $j$ ). Across all the competitors (a column of the switching matrix), we can think that there is a common (average) component related to the *clout* or *mass* of a brand and another series of differences related to these resultant velocities. Because mass times velocity is the momentum, we call the coefficient  $M_{jk}$  *momentum*. We can interpret momenta as follows:

- $M_{jk} = 1$  if the process is the zero-order,
- $M_{jk} < 1$  if brand  $j$  tends to lose attraction in submarket  $k$ , and
- $M_{jk} > 1$  if brand  $j$  tends to gain attraction in submarket  $k$ .<sup>6</sup>

<sup>6</sup>This specification is akin to Russell's (1992) and Russell and Kamakura's (1994) works. Russell defines the latent-symmetric-elasticity structure in which the asymmetric elasticity  $e_{ij}$  is represented as the product of a symmetric similarity measure,  $s_{ij}$ , and a column scaling factor,  $c_j$ , he calls *clout*. His definition of clout differs from the definition in Cooper's (1988) or Kamakura and Russell's (1989) studies.

Although the final attraction is a function of distance from the ideal point, momentum reflects the changes in force pushing each brand toward (or away from) the ideal point of each segment. Note that the ratio of the switching probabilities for two brands within a submarket is the ratio of their momenta:

$$(8) \quad \frac{p_{ijk}}{p_{jik}} = \frac{p_{ik} M_{jk} p_{jk}}{p_{jk} M_{ik} p_{ik}} = \frac{M_{jk}}{M_{ik}},$$

which is similar to the latent-symmetry specification in Russell's (1992) study.

We implicitly assume that, with respect to switching submarkets that contain more than one brand, there is no brand whose coordinates are the same as the ideal point; that is

$$(9) \quad x_{idk} \neq x_{dk}^* \quad \forall i \text{ in } k \text{ on } d \quad \forall d, k.$$

One way of thinking of this is, if a brand were located exactly on the ideal point in a switching submarket, this would be much more like a brand-loyal submarket—in contradiction to the spirit of the definition. Technically, this assumption is required to ensure that we need not take the logarithm of zero (cf. equations 1 and 2).

*ESTIMATION AND TESTS OF THE STRUCTURE OF COMPETITION AND PREFERENCE*

*Estimation*

We estimate the parameter set,  $\theta$ , that includes the submarket sizes,  $\{w_k\}$ ; momenta,  $\{M_{jk}\}$ ; association coefficients,  $\{\beta_{adk}\}$ ; and coordinates of ideal points,  $\{x_{df}^*\}$  so as to maximize the following likelihood function,  $L$ :

$$(10) \quad \max_{\{\beta_{adk}\} \{x_{dk}^*\} \{w_k\} \{M_{jk}\}} L \propto \prod_{i,j} p_{ij}^{n_{ij}},$$

given  $n_{ij}$ —the number of consumers who bought brand  $i$  at time  $t$  and brand  $j$  at time  $t + 1$ —under the three types of constraints,  $h$ , previously mentioned:  $\sum_{k=0}^K w_k = 1$ ,  $\sum_{i \in S_k} x_{idk}^2 + x_{dk}^{*2} = 1$ , and  $\sum_{j \in S_k} M_{jk} p_{jk} = 1$ . As was suggested by Aitchinson and Silvey (1960) and Luenberger (1984), we used the following successive approximation:

$$(11) \quad \begin{bmatrix} \theta_{r+1} \\ \lambda_{r+1} \end{bmatrix} = \begin{bmatrix} \theta_r \\ \lambda_r \end{bmatrix} - \kappa_r \begin{bmatrix} B_r & A_r \\ A_r & 0 \end{bmatrix}^{-1} \begin{bmatrix} l_r \\ h_r \end{bmatrix},$$

where  $\lambda_r$ 's are Lagrange multipliers evaluated at the  $r^{\text{th}}$  iteration,  $B_r$  is the Hessian matrix approximated by the BFGS algorithm at the  $r^{\text{th}}$  iteration,  $A_r$  is the matrix (evaluated at the  $r^{\text{th}}$  iteration) whose  $(i,j)^{\text{th}}$  element is  $\partial h_j(\theta)/\partial \theta_i$ ,  $l_r$  is the vector of the first derivatives of the log-likelihood with respect to all the parameters (evaluated at the  $r^{\text{th}}$  iteration), and  $\kappa_r$  is a scalar designed to assure improvement in log-likelihood at the  $r^{\text{th}}$  iteration.<sup>7</sup>

*Simulation Study of the Robustness of the Suggested Algorithm*

We conducted a simulation study to examine the robustness of parameter estimation against four factors: the number of attributes, or NAT, (2,3); the number of brands, or

<sup>7</sup>The derivatives are available from the author on request.

NBR, (10, 11, 12); the number of dimensions, or NDIM, (1,2); and the number of observations, or NOBS, (2000, 4000, 6000). Our criterion for robustness was the congruence coefficient developed by Tucker (1951), which is similar to the first canonical correlation between true and estimated configurations but is designed for ratio-scale configurations. The overall design of the simulation study was a  $2 \times 3 \times 2 \times 3$  ANOVA with five replications in each setting. Hence, in total we obtained 180 cases. We note four things. First, if two configurations match exactly, the congruence coefficient is equal to 1.0, otherwise it is between 0 and 1.0. Second, brand-attribute matrices were generated randomly for each replication on the basis of the standard-normal density in each cell of the design. Third, though the first three factors relate to parameter spaces, the last factor controls the size of the error variance, because the likelihood has a form of multinomial density whose variances are a function of sample size (i.e., the multinomial generalization of  $Npq$ , where  $N$  is the sample size). Fourth, in each setting, we assumed the existence of four submarkets in order to examine the robustness while taking into account the latent-class mixture. The congruence coefficient was calculated over all four submarkets.

The simulation scheme was the following. First, we generated a switching-probability matrix on the basis of a set of true parameters drawn from a standard-normal distribution for importance weights and ideal points and from a uniform density for submarket sizes and momenta. All true parameters were transformed in an appropriate way to satisfy the constraints given in Equation 4. Therefore, we are not aiming at the same target in each replication. The true values are different from one replication to the next. Second, we generated NOBS random numbers based on a uniform density and created a simulated switching matrix from these numbers according to the true switching-probability matrix. Third, we estimated the parameters from the simulated data. Fourth, we computed brand coordinates from the estimated parameters and calculated the congruence coefficient between the estimated and the true brand and ideal-point configurations. We replicated this five times in each setting.

The results of the simulation study were encouraging. Varying the NAT, NBR, or NOBS (error levels) did not seem to inhibit our ability to accurately recover the true structure. Furthermore, none of the two-way or higher-order interactions were significant. We have only one significant main effect, namely, the dimensionality (the mean value of the congruence coefficient for the cases of unidimensionality is .93 and that for the cases of two dimensions is .99). We observed the same result for the ANOVAs in which the dependent variable was the squared deviation between true and estimated switching probabilities. The same pattern of results, except for another significant main effect of the NBR, holds when the dependent variable is the mean-squared error of parameters. We conclude that the parameter estimation of our models based on the suggested algorithm is reasonably robust across ranges of NAT and NBR or NOBS (levels of errors). Recovery is more robust for two (or more) dimensions than for the unidimensional case. The traditional explanation for such a result is that when two points shift position on a line (so that one is closer to an ideal point) they must coincide, thereby producing something analogous to a singularity, whereas with two or more

dimensions, one point can move closer to the ideal without having to coincide with another.

#### *Criterion for Selecting the Best Market Structure*

The proposed model requires a priori hypotheses on market structure, compares them, and chooses the best. This model can be seen as a latent-class mixture of external preference-analysis models, as is indicated by Equation 7.

There now exist a rich variety of the mixture models—from the basic models in studies by Grover and Dillon (1985), Grover and Srinivasan (1987), Colombo and Morrison (1989), and Inoue (1993) to the latent-class binary-logit model (Dillon, Kumar, and de Borrero 1993), the latent-class multinomial logit model (Zenor and Srivastava 1993), the latent-class censored regression (Jedidi, Ramaswamy, and DeSarbo 1993), and the latent-class ML INDSCAL model (Winsberg and De Soete 1993; for a review, see Wedel and DeSarbo 1994). When it comes to latent-class mixture models, however, we cannot employ the well-known likelihood-ratio (LR) tests, the related tests, or criteria historically used for choosing an appropriate number of latent classes because of a violation of the regularity conditions (McLachlan and Basford 1988; Titterington, Smith, and Makov 1985). One way to determine the number of latent classes discussed by Titterington, Smith, and Makov (1985) and McLachlan and Basford (1988) is by:

$$(12a) \quad -2cLR,$$

where

$$c = (n - 1 - NP - .5K)/n,$$

$$LR = 2 \sum_{i=1}^I \sum_{j=1}^J n_{ij} \log(n_{ij}/\hat{n}_{ij}),$$

$n$  = the total number of observations,

$NP$  = the total number of parameters,

$K$  = the total number of latent classes,

$n_{ij}$  = the observed number of consumers in cell (i,j), and

$\hat{n}_{ij}$  = the estimated number of consumer in cell (i,j).

Alternatively, we can substitute  $\chi^2 = \sum_i \sum_j (n_{ij} - \hat{n}_{ij})^2 / \hat{n}_{ij}$  for the LR. It might be better, however, to apply the modified LR to information criteria as follows:

$$(12b) \quad AIC = LR + 2NP.^8$$

$$(12c) \quad CAIC = LR + NP(\ln n + 1).$$

$$(12d) \quad SBIC = LR + NP \times \ln n.$$

Also, we can formulate the following normalized measure bounded between 0 and 1:

$$(12e) \quad R^2 = \frac{LR_{null} - LR}{LR_{null}}.$$

Bozdogan (1994) argues strongly in support of using information criteria, despite their reliance on some of the same regularity conditions as does the likelihood function. We follow his recommendation.

<sup>8</sup>Bozdogan (1993) suggests using  $AIC = LR + 3NP$ , but this made no practical difference in our application.

### *Simulation Studies of the Robustness of Identifying True Market Structure*

We conducted a second simulation to investigate the robustness against misspecification of market structures. The previous simulation showed that if we had the correct brands in a particular segment, then our recovery of the true structure would not be hampered by changes in the underlying NAT, NBR, or NOBS. Therefore, the key questions in this second simulation are, Can we tell when we have too many or too few brands in a particular segment? and Can we tell when we have too many or too few segments? We examined these two questions on the basis of two simulation studies. We controlled the same four factors—two levels of the NAT, three levels of NBR, two levels of NDIM, and three levels of error (NOBS)—as we did in the previous simulation.

In both simulations, the dependent measures reflecting robustness are the information criteria, namely, Aikake's information criterion (AIC), Consistent AIC (CAIC), and Schwartz Bayesian Information Criterion (SBIC). In the first simulation, the generation scheme is the same as was previously used, but we calculated the information criteria under the following three market-structure hypotheses: true structure, overspecified structure, and underspecified structure. The true structure is the one on which each run is based. The overspecified structure has an additional brand placed in each of four submarkets, along with the brands corresponding to the true structure. The underspecified structure has one brand deleted from each submarket under the true structure. In the second simulation, the generation scheme is also the same, but the three market-structure hypotheses are as follows: The true structure is the one on which each run is based. The overspecified structure has an additional submarket, along with the four submarkets corresponding to the true structure. The underspecified structure does not have the last submarket under the true structure.

The results were encouraging. In the first simulation, of the 36 total patterns, we observed 33 cases in which AIC, CAIC, and SBIC were all minimized under the true hypotheses. We found only 1 of 36 cases in which the overspecified structure appeared best and only 2 of the 36 cases in which the underspecified structure appeared best. In the second simulation, of 36 total patterns, we observed 35 cases in which AIC was minimized under the true hypotheses and found only 1 of 36 cases in which the underspecified structure appeared best in terms of AIC. On the basis of CAIC and SBIC, we had 33 cases in which the true hypotheses were best and observed 3 cases in which the underspecified structure appeared best. Hence, we concluded that models are robust against misspecification of market structures.

### *Other Statistical Tests of Interest*

Following Bozdogan (1994), we still can count on information criteria regardless of the violation of the regularity conditions. Marketing managers and researchers might be interested in the following questions:

- Does hard-core-loyal submarket  $k$  exist?
- Does switching submarket  $k$  exist?
- Do consumers in submarket  $k$  perceive brand  $i$  differently from brand  $j$ ?
- Do consumers in submarket  $k$  employ a different attribute-evaluation rule than those in submarket  $k'$ ?

- Is an ideal point in submarket  $k$  different from that in submarket  $k'$ ?
- How many dimensions do consumers take into account in evaluating brands in submarket  $k$ ?

All of these questions can be examined on the basis of the information criteria described previously.

### *APPLICATION TO THE DATA IN HARSHMAN AND COLLEAGUES' (1982) STUDY*

We illustrate the proposed model and testing procedures by using trade-in data from the U. S. car industry. We need two data sets: a brand-switching matrix and brand-attribute matrix. We used the switching matrix published in Harshman, and colleagues' (1982) study. These data—collected in 1979 by Rogers National Research—involve 1,689,677 new car purchases of 106 different car models. The car traded in and the new car purchased are recorded in the standard 16 car categories: Subcompact/Domestic, Subcompact/Captive Imports, Subcompact/Imports, Small Specialty/Domestic, Small Specialty/Captive Imports, Small Specialty/Imports, Low-Price Compact, Medium-Price Compact, Import Compact, Midsize Domestic, Midsize Imports, Midsize Specialty, Low-Price Standard, Medium-Price Standard, Luxury Domestic, and Luxury Import. We removed Harshman and colleagues' fifth category (Small Specialty/Captive Imports), because there were no trade-ins from this category in 9 of the 16 categories, and there were few trade-ins in the remaining categories. The other data were developed by averaging (over the car models within each category) the *Consumer Reports* (1979) ratings for price, cost factor, overall length, front legroom, rear-seat room, engine size, horsepower, revolutions per mile, and overall maintenance. The resulting  $15 \times 9$  brand-attribute matrix is displayed in Table 2.

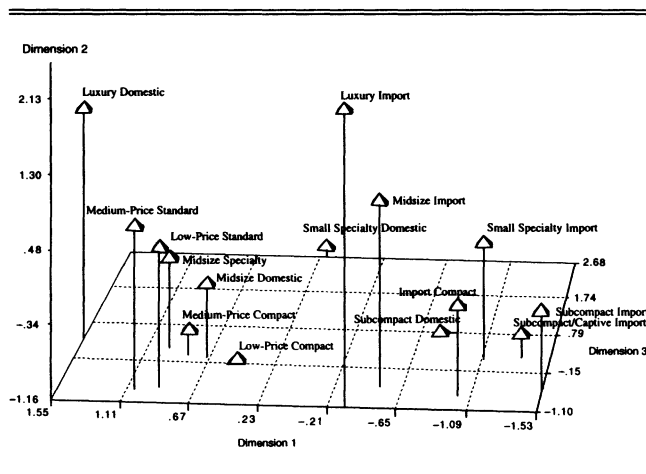
Because our simulation study warned against including too many attributes, we performed a factor analysis on the nine variables from *Consumer Reports* (1979). The parameters of the factor model are estimated by using the unweighted-least-square method, with the squared multiple correlations as prior estimates of communalities. The first differences in eigenvalue size indicated we should retain three factors. These factors accounted for approximately 98% of the positive eigenvalues.<sup>9</sup> An oblique simple-structure rotation—Promax (Hendrickson and White 1964)—aided interpretation. The first factor emphasizes overall length, rear-seat room, engine size, and horsepower, with strong negative weights for revolutions per mile and maintenance. Essentially, this factor presents the size of the cars from the Luxury Domestic and Medium-Price Standard categories to the Subcompact/Imports categories—as can be seen in the regression estimates of the factor scores (Tucker 1971) plotted in Figure 1. The pattern weights for the second factor emphasize price and cost, whereas the plot in Figure 1 goes, correspondingly, from the Luxury Imports and Luxury Domestic categories to the Low-Price Compact and Subcompact/Domestic categories. The third factor's weights

<sup>9</sup>There were three small, negative eigenvalues, as often happens when communalities are estimated. In such cases, the percentage of positive eigenvalues gives a more accurate reflection of the variance accounted for than does simply reporting the percentage of the trace (because that percentage can exceed 100%).

Table 2  
CAR-CATEGORY  $\times$  ATTRIBUTE MATRIX

Category	Price	Cost Factor	Overall Length	Front Legroom	Rear-Seat Room	Engine Size	Horsepower	Revolution Per Mile	Overall Maintenance
Subcompact/Domestic	4068	.88	171	41	24	16	90	2736	2.7
Subcompact/Captive Imports	4627	.89	161	40	24	10	78	2942	4.1
Subcompact/Imports	4972	.86	157	40	24	9	65	3322	4.6
Small Specialty/Domestic	4982	.87	184	95	24	23	116	2283	2.1
Small Specialty/Imports	6867	.86	165	41	23	11	84	3143	4.5
Low-Price Compact	4273	.88	195	41	29	24	111	2232	2.5
Medium-Price Compact	4252	.87	200	41	28	25	118	2242	2.6
Import Compact	6321	.87	173	41	28	11	85	3247	4.0
Midsize Domestic	5212	.84	204	42	28	26	122	2097	2.7
Midsize Imports	9513	.84	188	42	28	13	112	3061	4.3
Midsize Specialty	6199	.83	208	42	27	28	125	2095	2.7
Low-Price Standard	6416	.80	214	42	30	29	126	1865	3.5
Medium-Price Standard	6941	.80	217	41	30	28	130	1968	3.5
Luxury Domestic	13416	.77	213	42	30	35	157	1828	2.9
Luxury Imports	15994	.79	199	43	28	17	110	2895	5.0

Figure 1  
MAP OF ESTIMATED FACTOR SCORES  
FOR CAR CATEGORIES



are positive on front legroom, and substantially negative on rear-seat room and maintenance costs. This describes the Small Specialty/Domestic cars, such as the Camaro, Firebird, Mustang, and Corvette. They are long in front, short in the rear, and cost more to maintain than the comparable imports. Figure 1 shows this third dimension primarily differentiating this category from the others. Therefore, we use the names *Size*, *Price*, and *Specialty* for Factors 1, 2, and 3, respectively.

We present the details of three benchmark models and the final market-structure model in Table 3. The simplest null model is one that assumes symmetric switching in an unstructured market (i.e., the aggregate constant-ratio model with all momenta equal to 1.0). This hypothetical model has only six parameters and a likelihood ratio of 2.4 million and is the model against which the other models are judged. The asymmetric version of this model simply estimates momenta for each car in the universal market to reflect the overall asymmetry in the data. This model provides a significant improvement in CAIC (and  $R^2$  jumps from 0.0 to .28).

The next benchmark model is an asymmetric generalization of the Colombo-Morrison brand-loyalty model.

Colombo and Morrison (1989) assume that some of the non-switchers are truly brand loyal whereas others are well represented by a zero-order symmetric switching probability. This generalization treats loyal consumers in the same way as does the Colombo-Morrison model, but it uses momentum to reflect zero-order asymmetric switching for the switching segment. We see that this generalization of the Colombo-Morrison model represents a dramatic improvement over the symmetric and asymmetric null models.

Even this generalization of the Colombo-Morrison model still leaves us with but one segment to represent all styles of switching in these data. A single switching segment cannot represent the differentiation many consumers in 1979 made between what cars were imported and what were domestic car makes, or between the gas crisis-induced appeal of smaller cars over the more traditional, larger cars. The final market-structure model has the brand-loyal segments and the universal submarket, as was specified by the Colombo-Morrison model. It also has five segments that incorporate the major distinctions (imports and size), along with the more minor segments that were identified by residual analysis. The CAIC has dropped from over 1.7 million to 518,785 for the final model, and the  $R^2$  is just under .8. The dramatic improvement in fit provides strong evidence that different segments do have different (but overlapping) consideration sets.

As was previously mentioned, we cannot conclude that one proposed market structure is better than another merely based on the LR. However, following Bozdogan's (1993) argument and considering the advantage on all the information criteria, we selected our final market structure over all the benchmark models.<sup>10</sup>

<sup>10</sup>This final model also is superior to models used for technical comparison. If we add a switching segment to the final model, CAIC increases to 880,046. If we drop the weakest switching segment, CAIC increases to 1,433,467. If we add one dimension to the most important switching segment in the final model, CAIC increases to 1,175,726. If we drop one dimension from the weakest switching segment, CAIC increases to 1,988,918. The problem of local optima was handled by using 30 different random starting configurations. Three of the solutions converged to the best value reported here. The algorithm converged in under 28 iterations on average—with 90% of the configurations requiring 36 or fewer iterations to converge.



**Table 3**  
COMPARISON OF THE RESULTS OF MARKET-PREFERENCE-STRUCTURE HYPOTHESES

<i>Symmetric Unstructured Hypothesis</i>				
	<i>Dimension 1</i>	<i>Dimension 2</i>	<i>Number of Parameters</i>	<i>6</i>
Ideal Point	-.626	-.235	<b>LR</b>	2,488,243
Size	-.688	-.177	<b>AIC</b>	2,488,255
Price	.747	-.335	<b>CAIC</b>	2,488,286
Specialty	.484	.733	<b>SBIC</b>	2,488,280
			<b>R<sup>2</sup></b>	0.0
<i>Asymmetric Unstructured Hypothesis</i>				
	<i>Dimension 1</i>	<i>Dimension 2</i>	<i>Number of Parameters</i>	<i>20</i>
Ideal Point	1.502	-.526	<b>LR</b>	1,881,588
Size	2.290	-1.952	<b>AIC</b>	1,881,628
Price	.023	1.495	<b>CAIC</b>	1,881,732
Specialty	-.914	.642	<b>SBIC</b>	1,881,712
			<b>R<sup>2</sup></b>	.244
<i>Asymmetric Colombo-Morrison Market-Structure Hypothesis</i>				
	<i>Dimension 1</i>	<i>Dimension 2</i>	<i>Number of Parameters</i>	<i>34</i>
Ideal Point	.376	-.106	<b>LR</b>	1,730,210
Size	.040	.336	<b>AIC</b>	1,730,278
Price	-.652	.650	<b>CAIC</b>	1,730,456
Specialty	.402	-.366	<b>SBIC</b>	1,730,422
			<b>R<sup>2</sup></b>	.305
<i>Asymmetric Final Market-Structure Hypothesis</i>				
	<i>Dimension 1</i>	<i>Dimension 2</i>	<i>Number of Parameters</i>	<i>93</i>
Ideal Point	-.082	.476	<b>LR</b>	518,113
Size	.956	.752	<b>AIC</b>	518,299
Price	-.274	-.744	<b>CAIC</b>	518,785
Specialty	.240	-.130	<b>SBIC</b>	518,692
			<b>R<sup>2</sup></b>	.792

**Table 4**  
SUBMARKET SIZES AND MOMENTA

	<i>Submarket 0</i>	<i>Submarket 1</i>	<i>Submarket 2</i>	<i>Submarket 3</i>	<i>Submarket 4</i>	<i>Submarket 5</i>	
<b>W<sub>k</sub> for Switching</b>	<b>Submarket</b>	.330*	.042	.235	.087	.091	.018
<i>Category</i>	<i>W<sub>k</sub> for Loyal Submarket</i>	<i>Subcompact &amp; Small</i>	<i>Domestic</i>	<i>Subcompact Small, Midsize, &amp; Compact</i>	<i>Midsize, Standard &amp; Luxury</i>	<i>Small Specialty, Midsize, &amp; Luxury</i>	
Subcompact/Domestic		.51	1.88	23.06	1.16	—	—
Subcompact/Captive Imports	.001	.51	.53	—	.31	—	—
Subcompact/Imports	.013	3.63	.13	—	1.92	—	—
Small Specialty/Domestic		2.74	.89	1.70	1.52	—	.30
Small Specialty/Imports	.002	.47	2.28	—	.69	—	4.53
Low-Price Compact	.011	.39	—	1.40	.78	—	—
Medium-Price Compact	.005	.19	—	1.68	.30	—	—
Import Compact		.15	—	—	.42	—	—
Midsize Domestic	.027	.66	—	.33	2.35	.60	.39
Midsize Imports	.001	.65	—	—	2.53	.06	1.12
Midsize Specialty	.002	3.00	—	2.11	—	.39	.50
Low-Price Standard	.026	.68	—	.95	—	1.22	—
Medium-Price Standard	.035	.75	—	.55	—	2.13	—
Luxury Domestic	.039	.87	—	.50	—	1.05	—
Luxury Imports	.036	.50	—	—	—	.54	1.03

\*All estimates are significant.

In Table 4, we summarize the estimates of the submarket sizes and the momenta under the final market-structure hypothesis. All parameters are significant ( $p < .05$ ) on the basis of the standard errors derived from the maximum-likelihood estimation. Several findings are worth noting:

•Three categories (Subcompact/Domestic, Small Specialty/Domestic, and Import Compact) do not have their own loyal submarket. These categories probably represent some buyers' first new car or their first, new second car—a transitional phase in car ownership—rather than categories to which buyers are loyal.

**Table 5**  
ESTIMATES OF PREFERENCE-STRUCTURE PARAMETERS\*

	<i>Dimension 1</i>	<i>Dimension 2</i>
<b>Submarket 0</b>		
Ideal Point	-.082	.476
Size	.956	.752
Price	-.274	-.744
Specialty	.240	-.130
<b>Submarket 1</b>		
Ideal Point	.300	**
Size	5.096	**
Price	-1.021	**
Specialty	-5.293	**
<b>Submarket 2</b>		
Ideal Point	.102	-.034
Size	1.519	1.325
Price	-1.113	-.308
Specialty	-.154	.522
<b>Submarket 3</b>		
Ideal Point	-.318	-.204
Size	.3878	.464
Price	1.116	1.121
Specialty	.463	.601
<b>Submarket 4</b>		
Ideal Point	-.394	**
Size	.746	**
Price	-.092	**
Specialty	-1.189	**
<b>Submarket 5</b>		
Ideal Point	.160	**
Size	.538	**
Price	-.675	**
Specialty	-.064	**

\*All standard errors < .001, and all t-Statistics > 20.

\*\*One-dimensional solution.

- The Low-Price and Medium-Price Standard cars, the Midsize Domestic cars, and the Luxury Domestic cars have large loyal submarkets. These three sectors represent the traditional American car market as viewed by Detroit in the 1950s and 1960s—everyone with standard-size cars, with the market partitioned on what a buyer could afford. Yet, by the end of the 1970s, this market had eroded to the point that these loyal submarkets constituted collectively under 13% of the buyer population. Furthermore, the momenta of these segments in the universal market and the domestic submarket are shrinking.
- The generalization of the Colombo-Morrison model posits that just the loyal submarkets and the universal market (Submarket 0) exist. If we sum the weights for these segments, we see that they reflect approximately 53% of the combined loyal and switching segments in our final model.
- The universal submarket is the largest ( $w_0 = 33\%$ ), and the domestic car submarket is the second largest ( $w_2 = 23.5\%$ ). In those two large submarkets, note the rapid increase of the small cars. Subcompact/Import cars ( $M_{30} = 3.63$ ) have the largest momentum in the universal submarket, and the Subcompact/Domestic cars ( $M_{12} = 23.06$ ) have by far the largest momentum in the domestic submarket.
- We see that Subcompact/Captive Import and Import Compact cars are losing momentum in all markets.
- Finally, we observe some competitive realignment—car categories are gaining momentum in some submarkets while dramatically losing momentum in others. For example, Subcompact/Import cars are entering the mainstream—gaining momentum in the universal market ( $M_{30} = 3.63$ ) while losing

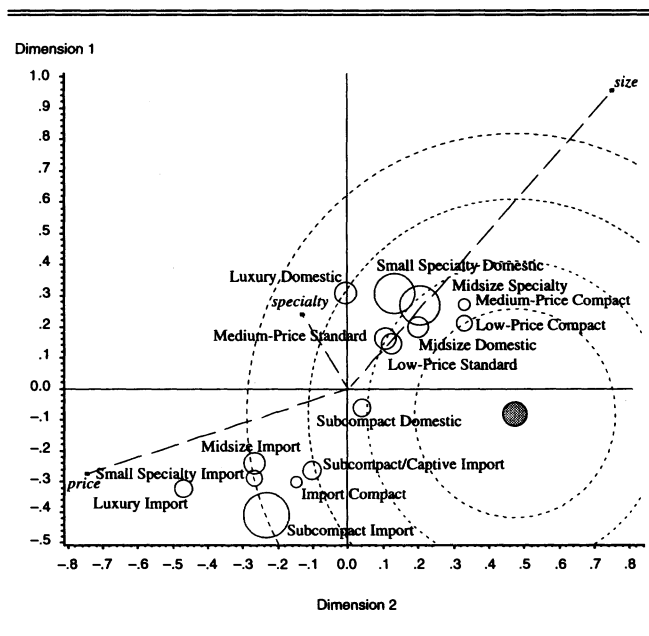
momentum among buyers who consider only the smallest cars ( $M_{31} = .13$ ). Midsize Domestic cars are becoming more niche players—losing momentum in the universal market ( $M_{90} = .66$ ) and domestic market ( $M_{92} = .33$ ), but gaining momentum in their battle with models of the same or smaller sizes ( $M_{93} = 2.35$ ). Simply tracking the momentum of brands within each submarket provides marketing managers with valuable insights into how well marketing goals have been achieved.

In Table 5, we give the parameter estimates and standard errors for all submarkets in the final model. The standard errors indicate that all coordinates, vectors representing the attribute factors, and ideal points are statistically significant (i.e., different from zero) in the benchmark models. In Figures 2 and 3, we map the competition in universal market ( $S_0$ ) and the domestic market ( $S_2$ ).<sup>11</sup> In each map, the ideal point is shaded by cross hatching, and the concentric circles of dotted lines represent isopreference contours centered on the ideal point. The size of each circle is proportional to the momentum—with the ideal point represented as having a momentum of 1.0 for comparative purposes. The length of the vectors representing the attribute factors indicates the relative importance (explanatory power) of each of these factors in determining the map for each segment or submarket. We interpret the map for each of these illustrative markets in turn.

In Figure 2, we show the universal market ( $S_0$ ). Price and size are the dominant attributes in the universal market. The price vector draws all the foreign-car categories down toward the lower left of the figure, because, on an average, the foreign cars are more expensive than their domestic counterparts. The size vector draws the domestic car categories up to the right of this figure, because, on an average, the domestic models are larger than the corresponding for-

<sup>11</sup>Maps of the other submarkets are available from the authors on request.

**Figure 2**  
THE UNIVERSAL MARKET ( $S_0$ )

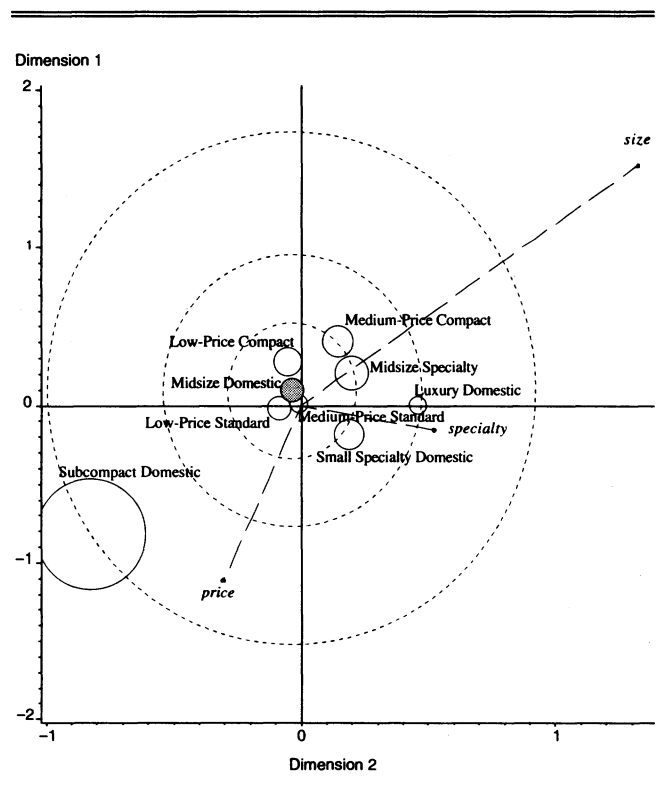


eign models. Therefore, the importance vectors combine to divide the overall market into domestic and foreign subparts. Among the domestic car categories, Low-Price Compact cars have a slight edge on Medium-Price Compact cars (in proximity to the ideal point and momentum). Low-Price Standard cars and Medium-Price Standard cars are competitively close, with the edge in proximity to the ideal point going to the Low-Price Standard cars. Midsize Domestic cars battle Midsize Specialty and Small Specialty cars. Although the Midsize Domestic cars are slightly closer to the ideal point, the momentum of these two rival segments appears to be a clear threat. The Luxury Domestic cars are further from the ideal point (obviously related to the importance of price in this map), but clearly a partner in what is largely the domestic side of the universal market. The Subcompact Domestic cars are somewhat isolated between the largely domestic and the largely imported parts of the universal market. Note that all the car segments on the largely imported side of the market are substantially further away from the ideal point. The Subcompact/Captive Imports are the closest to the ideal point but are about as far from the ideal point as Luxury Domestic cars (the most remote in the largely domestic group). The Subcompact/Imports are dramatically gaining momentum in this overall market. Although these cars are about the same distance from the ideal point as the Small Specialty/Imports and Midsize Imports, the large momentum is a warning signal to their competitors. The Low-Price Compact cars are closer to the ideal point, but the large momentum of the Subcompact/Imports on one side, and the better position and momentum of Subcompact/Captive Imports on the other side underscore the vulnerability of the Low-Price Compact car segment. The Luxury Import cars are competitively aligned with this block but just further removed from the ideal point because of price.

For the estimated 23.5% of the market that considers only domestic cars, Figure 3 represents the forces underlying the trade-in data. Notice that the ideal point is at the center of the competitors. Size is the dominant factor (and the size vectors point away from the Subcompact Domestic cars). The center of the map shows the battle between the Midsize Domestic cars, Medium-Price Standard cars, and Low-Price Standard cars, with the Low-Price Compact cars off on their own but still close to the ideal point. The ring of competitors just beyond that includes the highly competitive Medium-Price Compact cars and the Midsize Specialty cars—with the Small Specialty cars being equidistant from the ideal point, but less intensely caught up in the rivalry between the other two segments. The Luxury Domestic cars are relatively aligned with these three segments but are further away from the ideal point. The looming threat is the Subcompact Domestic segment, which shows large relative momentum but is both remote from the ideal point and aligned far from the other competitors in the domestic car market.

In summary, by recognizing the heterogeneity of consideration sets, ideal-points, brand positions, and differences in the importance of underlying attributes across submarkets and by tracking the momentum of brands within each submarket, we obtained a much more fine-grained picture of the multitude of competitive threats and market opportunities facing each model. We believe managers should establish market goals and review marketing plans, taking into

Figure 3  
SUBMARKET 2—DOMESTIC CARS



account each of the submarkets in which their car model competes. Reviewing these, one at a time, could reveal where a solution to problems in one submarket might create problems in another. This kind of review will hopefully lead to the evolution of plans that possess greater synergies for brands that encounter multifaceted competition.

#### FUTURE EXTENSIONS

We are interested in two direct extensions of this work. An important extension concerns modeling other modes of structural change. According to Golembiewski, Billingsley, and Yeager (1976), we can distinguish three types of change:  $\alpha$ -change,  $\beta$ -change, and  $\gamma$ -change.<sup>12</sup> Applying their framework to our model, we obtain the following:

When the frame of reference remains unchanged, but the brands or ideal points shift, we have an  $\alpha$ -change:

<sup>12</sup>Golembiewski, Billingsley, and Yeager (1976) define the three types of change as follows:  $\alpha$ -change involves a variation in the level of some existential state, given a constantly calibrated measuring instrument related to a constant conceptual domain. For us, this would be equivalent to the dimensions and importance of the space remaining the same, while some brands or ideal points were repositioned.  $\beta$ -change involves a variation in the level of some existential state, which is complicated by some intervals of the measurement continuum associated with a constant conceptual domain having been recalibrated. For us, this means a change in the importance of some of the dimensions. The  $\gamma$ -change involves a redefinition or reconceptualization of some domain,—a major change in the perspective or frame of reference within which phenomena are perceived and classified, in what is taken to be relevant in some slice of reality. For us, this implies new importances and possibly new dimensions to the space.

$$(13a) \quad \alpha - I: \delta_{ik} = \sqrt{\sum_{d=1}^{D_k} (x_{id} - w_{dk} x_d^*)^2} = \sqrt{\sum_{d=1}^{D_k} (x_{id} - x_{dk}^*)^2}.$$

$$(13b) \quad \alpha - II: \delta_{ik} = \sqrt{\sum_{d=1}^{D_k} (w_{dk} x_{id} - x_d^*)^2}$$

$$= \sqrt{\sum_{d=1}^{D_k} (x_{idk} - x_d^*)^2}.$$

When the underlying values or importances of the dimensions change we have a  $\beta$ -change. The weighted Euclidean model (Winsberg and de Soete 1993) reflects this market structure:

$$(14) \quad \beta: \delta_{ik} = \sqrt{\sum_{d=1}^{D_k} (w_{dk} x_{id} - x_d^*)^2}$$

Our model, on the other hand, represents the most complex change with different brand spaces and different ideal points from submarket to submarket. We can express the model as follows:

$$(15) \quad \alpha - \beta: \delta_{ik} = \sqrt{\sum_{d=1}^{D_k} w_{1dk} (x_{id} - w_{2dk} x_d^*)^2}$$

$$= \sqrt{\sum_{d=1}^{D_k} (x_{idk} - x_{dk}^*)^2}$$

From this perspective we have started with the most complicated model. The extension to simpler modes of change, namely,  $\alpha$ - and  $\beta$ -changes, not only gives us more varieties of change but also reduces the number of parameters.

Another worthwhile extension involves the comparison of our current approach to the representation of heterogeneity with the compound-distribution approaches. In our model, the heterogeneity of choice probabilities is dealt with in a discrete way—using a special case of latent-class analysis. Alternatively, we could deal with the heterogeneity in a continuous manner—using the compound (conjugate) distributions such as the Beta-binomial model (Colombo and Morrison 1988), Dirichlet-multinomial model (Jain, Bass, and Chen 1990), or Negative Binomial Distribution (NBD) (Gamma-Poisson) model (Morrison and Schmittlein 1988). We believe that comparison of the discrete (latent-class) and continuous (NBD) approaches would help us know if these are complementary methods or competitive modeling frameworks for capturing the same variability in behavior.

Perhaps work with these distributions also could help deal with the issue of variety seeking over time. Although our illustration concerns durables, the extension of this approach to categories of frequently purchased branded goods will need to deal more specifically with the drive for variety.

Another key limitation of all latent-structure methods concerns the reality of latent segments. Within our illustration we have no doubt that some people consider only

domestic cars, whereas others consider only some classes of smaller cars or some segments of more luxurious cars. In general, however, the reality of a latent class should be backed up by other research before major marketing-strategy decisions are based on it. In our model, this amounts to doing research on what the consideration sets are that consumers use. Such research also would be helpful in the heuristic process of specifying the final structure to be estimated by our maximum-likelihood scheme.

A final limitation is reflected in the absence of a validation data set. Because of the momentum we observed within segments and the shocks to car-buying behavior that have occurred since these data were collected, we have little idea how much stability to expect in these segments. Nevertheless, the data that could address such issues were not collected. This limitation should be addressed in any further research using this model.

In summary, we have presented a model that marries two data types—switching data and attribute data—each of which is crucial for understanding different aspects of market structure. Five key insights into market structure result from this effort. First, we obtain a segment-by-segment account of the differences in consideration sets or competitive groups. Second, we obtain a segment-by-segment account of the differences in evaluative criteria. Third, we obtain maps. Fourth, we obtain different ideal points for each segment. Fifth, we obtain a segment-by-segment account of which brands are gaining and which are waning. No other model or method offers the collective insights that result from this effort.

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