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WHO COMPETES WITH WHOM? A DEMAND-BASED PERSPECTIVE FOR IDENTIFYING AND REPRESENTING ASYMMETRIC COMPETITION

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A host of strategic management and marketing issues, including competitive analysis and strategic decision making, hinges on accurately identifying and representing competitive market structures. It is readily acknowledged that competitive market structures are typically asymmetric; namely, one firm may actively compete with another in a given market but not vice versa. However, empirical efforts to assess these competitive asymmetries have been lacking in the strategy literature. We propose a new spatial methodology to identify and represent asymmetric competitive market structures. Specifically, we devise a new stochastic multidimensional scaling procedure that is calibrated from actual consumer consideration/choice sets to estimate and uncover competitive asymmetries. The proposed methodology can be effectively employed in the analysis of appropriate data from either demand- or supply-side approaches to assess competitive market structure. We illustrate our proposed methodology with survey data collected from two different commercial applications: one from the U.S. luxury automobile market and the other from the U.S. portable telephone market. We contrast the findings of the proposed methodology against traditional symmetric approaches for identifying and representing competitive market structures, and discuss the respective strategic insights.

INTRODUCTION

There is a growing recognition in strategic management and marketing literature that competitive market structures are inherently asymmetric in that the degree to which one firm competes with another is not typically the same as the degree to which the second firm competes with the first (e.g., Amit and Schoemaker, 1993; Carpenter *et al.*, 1988; Chen, 1996). For example, a high market-share market leader may not choose to compete actively with a much smaller market niche player given the limited expected pay-off in winning additional small shares of the marketplace, whereas the small niche player may actively target the much larger market leader in its competitive strategy. This competitive asymmetry phenomenon appears often across various industries. Along similar lines, Collis (1991) argues that even when faced with the same competitive situation, firms possess different resources and approach the competitive situation differently. Likewise, using taxonomic mental models, Porac and Thomas (1990) suggest that even within industries, firms vary in the manner in which they define competitors. Despite this growing recognition among strategy scholars that competitive market structures are asymmetric, attempts to identify and examine these competitive asymmetries have been somewhat lacking.

The strategic ramifications of competitive asymmetries are immense. The business literature is littered with a plethora of examples of such

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competitive asymmetry. Decades ago, railway firms, for example, defined competitors as other railway firms and did not explicitly consider other transportation firms, such as automobile manufacturers, as competitors, whereas automobile manufacturers considered railway firms to be their major competitors. In his famous article, Levitt (1975) uses this competitive asymmetry between railways and automobiles to illustrate 'marketing myopia,' a possible outcome of competitive asymmetry. Decades later, the inability of U.S. firms in industries as diverse as automobiles and electronics to identify competitive threats from Japanese firms provides other examples of competitive asymmetry, wherein the Japanese considered the U.S. firms as the primary competitive threat (e.g., Hamel and Prahalad, 1990; Yates, 1984). More recently, the lackadaisical response of Barnes & Noble to the competitive threat of Amazon.com has provided another example of asymmetric competition.

The two dominant perspectives on competitive market structures—the supply-based perspective largely developed in strategic management literature (e.g., Chen, 1996) and the demand-based perspective espoused in marketing literature (e.g., Carpenter *et al*., 1988)—actively recognize the notion of competitive asymmetry. For example, Chen (1996: 116) notes that the 'firm-specific conceptualization of competitors and competitive relationships further suggests that the competitive relationship between a pair of firms is asymmetric, depending on which competitor is the focal firm under consideration.' Along similar lines, Carpenter *et al*. (1988: 393) theorize asymmetric competition to occur when 'the effects of a brand's marketing actions are distributed among its competitors out of proportion of their market share.' Although the supply- and demand-based perspectives vary in terms of the information they consider (information from firms and managers and information from customers, respectively), the two perspectives seem to address the same basic challenge, namely, uncovering competitive market structures. Both perspectives recognize competitive market structures as asymmetric; however, as Chen (1996: 117) remarks, 'with only a few exceptions, this concept [competitive asymmetry] has not been addressed in the strategy literature.' Along similar lines, although the marketing literature recognizes the existence of competitive asymmetries, most empirical studies treat competition as symmetric.

With the objective of empirically uncovering asymmetric competitive market structures, we integrate relevant aspects of the literature on supply- and demand-based market structures. We use the theoretical insights gained from this integration to propose an empirical approach for identifying and representing within-industry competitive market structures and competitive asymmetry. In addition, we illustrate our proposed methodology from a demand perspective using data collected from consumers, although the methodology is sufficiently general to include appropriate data from the supply side as well. As we suggest through our integration of supply- and demand-based perspectives, employing insights from both perspectives should be the most appropriate approach to uncover competitive asymmetry and avoid myopic strategic thinking.

We propose a new statistical spatial technique and illustrate it with data from consumer consideration/choice sets (hereafter choice sets), which provide time- and situation-specific information about consumer preferences and the brands they perceive as competitors (Roberts and Lattin, 1991), to uncover market structures and assess the asymmetric nature of competition (DeSarbo and Jedidi, 1995). In turn, for the empirical part of our research, we operationalize asymmetric competition to occur when the probability that a brand is in the consideration set of a competitor's brand is different from the probability that the competitor brand appears in the consideration set of this brand. Specifically, we develop a new stochastic multidimensional scaling (MDS) technique to extract firm-/brand-specific market structures and asymmetric competitive maps from the information derived from consumer choice sets. As the results from our illustrations of the model with data from the U.S. luxury automobile and portable telephone communications industries show, competitive market structures are asymmetric, and uncovering these asymmetries provides critical information for competitor analysis and strategic decision making.

We organize this manuscript along the following lines: In the next section, we first review the competitive market structure literature that suggests that firms are heterogeneous and competitive market structures are asymmetric, and then lay out the reasons for using consumer choice sets to assess market structures and competitive asymmetry. Subsequently, we present the technical details of our proposed model and discuss the model selection strategy with various options. We also propose a means to represent asymmetric competitive market structures spatially that is efficient, easy to comprehend (e.g., DeSarbo and Hoffman, 1986), and applicable to any industry. Subsequently, we describe two empirical studies involving the U.S. luxury automobile and portable telephone communications industries and contrast the results from both traditional symmetric methods to identify market structures and our proposed methodology which explicitly models competitive asymmetry. We also create a statistical maximum likelihood framework that enables us to test symmetric vs. asymmetric spatial representations of competitive market structure formally. In the final section, we discuss the implications of our research for theory and practice.

CONCEPTUAL BACKGROUND

Competitive market structures and competitive asymmetry

Market structure, in its broadest sense, captures the configuration of buyers and sellers in a marketplace, including the competitive structures among the buyers and the sellers and the relationships that they may have with any important institutional body, such as regulatory agencies and trade associations. In contrast, competitive market structures primarily capture the configuration of firms that compete with one another at a given level of the value chain. Thus, competitive market structures might be operationalized as the competition among sellers who provide substitutable products.

Competitive asymmetry exists when the degree and/or direction of competition between two firms is not equal, as when Firm A competes more intensely with Firm B than Firm B competes with Firm A. With this general conceptualization of asymmetric competition, we can operationalize competitive asymmetry on the basis of the research question under study. When examining multimarket competition, we might theorize that competitive asymmetry exists if Firm A has operations in a subset of markets in which Firm B has operations (e.g., Gimeno and Woo, 1999). Thus, competition between a national airline (e.g., Northwest) and a regional airline (e.g., Alaska Air) could be seen as asymmetric; for Alaska Air, Northwest is the main competitive threat, but Northwest might consider other national airlines such as Delta to be its primary competitors. Similarly, when studying brand competition, researchers theorize competitive asymmetry exists when the cross-price elasticity of two firms are not equal (e.g., Blattberg and Wisniewski, 1989). For this research, we employ operationalizations based on consumer choice sets.

Although research on assessments of competitive asymmetry is beginning to emerge, theoretical developments related to why they exist have been lacking. Because human decision making in the development of market structures involves various areas, specifically, consumer, managerial, and stakeholder (e.g., shareholders, regulators, trade associations) decision making, competitive asymmetries may become manifest due to the systematic biases in these decision-making processes. Literature in economics (e.g., Simon, 1957) on bounded rationality and satisficing and in psychology (e.g., Kahneman, Slovic, and Tversky, 1982) on heuristics and biases in human judgments, which discusses the manner in which human decisions may not be rational, can be used to establish the theoretical basis for competitive asymmetry.

Systematic biases in human judgments come in the form of cognitive biases, such as when decision-makers use information that is easily available (e.g., vivid events), or motivational biases, when decision-makers may have diverse goals (e.g., Bazerman, 2002; Gilovich, Griffin, and Kahneman, 2002). When making decisions, humans resort to selective information search, followed by selective encoding of the information searched; only selective components of the encoded information are retrieved. The importance of human perception and its inherent biases has been recognized in the context of product market dynamics and competitive market structures (e.g., Porac and Thomas, 1990; Rosa *et al.*, 1999). Thus, we suggest that because human cognition plays a critical role in perceptions (which lead to decisions), such systematic biases in human judgment might result in competitive asymmetry.

In addition to systematic biases in human judgments, it is also important to recognize that human judgments are embedded in a larger societal context that determines the validity and legitimacy of judgments and in which cultural norms, sociopolitical systems, and social networks play critical roles. Cultural norms such as the *Keiretsu* system in Japan for risk hedging (firms erect barriers to entry across the value chain; e.g., Ahmadjian and

Lincoln, 2001) or the emphasis on brand name products in certain reference groups should influence the manner in which decision-makers, including managers and consumers, perceive competitive offerings (e.g., Abrahamson and Fombrun, 1994). Sociopolitical systems involve the influence of societal institutions such as legal (e.g., antitrust laws) and normative (e.g., the homogenization of cognitive frames due to formal educational systems) institutions on competitive dynamics (e.g., DiMaggio and Powell, 1983). For example, public sentiments and chain store laws made it difficult for retailers with a large number of stores to compete with single-store competitors during the first half of the twentieth century (Grewal and Dharwadkar, 2002). Finally, social networks determine the quantity and quality of information a decision-maker receives, which leads to his or her structural embeddedness (Granovetter, 1985). The quantity and quality of information are likely to affect the manner in which sociocognitive competitive dynamics are conceptualized (Rosa *et al.*, 1999), the criteria used for evaluating competitors (Porac and Thomas, 1990), and the accuracy with which judgments on competitors are held (Koehler, 1994). Thus, theories related to human judgments and organizational embeddedness should provide fruitful avenues for studying the emergence and consequences of competitive asymmetry.

Dominant perspectives on competitive market structures

Supply-based perspectives of market structures grew out of the industrial organization (IO) school, which espouses the importance of industry structure by observing that profitability depends on industry concentration (Scherer and Ross, 1990). Strategy researchers drew heavily from the IO school (e.g., Barney, 1986) but questioned the assumption that all firms in the industry are *de facto* competitors (e.g., Cool and Schendel, 1987; Fiegenbaum and Thomas, 1990; Hatten, Schendel, and Cooper, 1978). Thus, even though strategic group analysis does not claim that competitor analysis is its primary objective (Hatten and Hatten, 1987), research on strategic groups relies on the premise that firms within a strategic group compete with one another. Although strategic group research explicitly recognizes that competition within an industry is asymmetric, such that it varies from one strategic group to another, these researchers implicitly assume that competition within strategic groups is symmetric.

Building on the strategic groups literature, decision-making scholars argued for incorporating managerial social and psychological factors into competitor identification and analysis (Porac and Thomas, 1990; Zajac and Bazerman, 1991). This particular stream of research suggests that the relevant competitors and market structures depend on managerial perceptions. If competitors are established according to the known perspective of all firms in an industry (or strategic group), competitive asymmetries should be easily identified. For example, competitive asymmetry would exist if Firm A identifies Firm B as a competitor but Firm B does not actively perceive Firm A as its competitor. However, the biases in human decision making creep into managerial attempts to define market structures through processes of competitive enactment, as manifested in competitive blind spots (Bazerman, 2002). In their study of Scottish knitwear manufacturers, Porac, Thomas, and Baden-Fuller (1989) conclude that Scottish knitwear manufacturers, who account for only 3 percent of the global market share, tended to identify only Scottish manufacturers as their competitors, thereby ignoring 97 percent of the world market. The U.S. automobile industry and its 'Detroit mind' illustrates the universality of this problem (Yates, 1984).

From a demand perspective, market structure is viewed 'as the *set of products* judged to be substitutes within those usage situations in which similar patterns of benefits are sought, and the *customers* for whom such usages are relevant' (Day, Shocker, and Shrivastava, 1979: 10; also see Day, 1981). For example, one could consider all cars (brands) in the luxury automobile market as competitors, but consumers may not consider all those brands when making their choice decisions; thus, only the brands considered represent the '*set of products* judged to be substitutes.' To assess competitive market structures, marketing researchers have used various types of consumer data, including those related to (1) perceived similarities between brands (DeSarbo and Manrai, 1992), (2) elasticity of marketing mix elements (Russell and Bolton, 1988), (3) brand-switching probabilities (Carpenter and Lehmann, 1985), (4) preferences/choices (DeSarbo, Manrai, and Manrai, 1993), and (5) information on choice sets (DeSarbo and Jedidi, 1995).

Some headway has been made through the demand-based perspective to discern competitive asymmetry. For example, relying on aggregate brand-level data, Blattberg and Wisniewski (1989) demonstrate the asymmetric patterns of price competition between high-price, high-quality brands and other brands in the same price–quality tier. This asymmetric switching between high- and low-quality brands is fairly well documented in the marketing strategy literature (e.g., Allenby and Rossi, 1991; Kamakura and Russell, 1989). Similarly, in developing their aggregate market share model, Carpenter *et al*. (1988: 393) view competition as asymmetric when 'the effects of a brand's marketing actions are distributed among its competitors out of proportion of their market shares.' These authors examine the profit implications of asymmetric brand competition models and shed light on the resulting resource allocation decision. Models that use individual consumer-level preference data similarly theorize competitive asymmetry in terms of the differences in the influence of two brands on each other (e.g., Cooper and Inoue, 1996). Typically, competitive asymmetry exists when the effect of a brand on its competitor is not necessarily the same as the effect of that competitor on the brand.

Comparing and integrating supply- and demand-based perspectives

Both supply- and demand-based perspectives intend to address the same issue, that is, to uncover competitive market structures. Thus, it comes as a surprise that for decades the perspectives were developed independent of each other. As our subsequent arguments demonstrate, despite the fundamental differences between them, the two perspectives are more complements than substitutes and richer insights can be gained by integrating them.

The primary differences between the two perspectives relate to (1) the unit of analysis and (2) the source of information (data). In terms of the unit of analysis, supply-based perspectives usually focus on a firm or strategic business unit, whereas demand-based approaches tend to emphasize brands or brand portfolios. The main issue that arises from difference in the unit of analysis relates to data aggregation. For example, assume that two firms have a similar scale of operations in a given industry with one dominant brand. Furthermore, assume that the dominant brands of the two firms address different market segments in the industry. A firm-level analysis would indicate that they compete intensely with each other because they have a similar scale of operations, but brand data clarify that the two firms are not primary competitors. Thus, in this example, the aggregate (firm-level) approach fails to uncover the true competitive market structure.

However, the firm-level approach sometimes may work better than a more disaggregated approach. For example, consider a market with three segments in which profitability and volume vary across the segments, and assume that the two focal firms possess two brands each. Furthermore, assume that the first firm serves the first two segments and the second firm serves the last two segments. Thus, the two firms actively compete in the second segment, but competition between them likely goes beyond this second segment as there probably are overlaps across the segments and the firms could use profits from the first and third segments to feed their rivalry in the second segment. The challenge for the brand-level approach here in quantifying competition is immense. What should be the basis of aggregation—segment market shares, volume, or profits? Even if the two firms had brands in the same segment, the issue of the bases of aggregation would still be key. Another pertinent instance would arise in the case of multimarket competition which occurs when firms compete in several geographic and/or product markets (e.g., Gimeno and Woo, 1999). In such cases, when firms asymmetrically overlap across markets, both the firm- and brand-level perspectives fail to provide a true portrait of competition. Clearly, if insights could be gleaned from both approaches, a more complete picture of competitive market structures would emerge.

The second major difference between the two perspectives pertains to sources of data. Supply-based perspectives rely on primary or secondary data of firm characteristics (e.g., size), strategy (e.g., economies of scale), and performance (e.g., return on assets) to identify (usually using cluster analysis) firms with similar levels on the chosen variables such that the identified firms are more likely to compete with each other (i.e., belong to the same strategic group). Recently, to incorporate the managerial decision process, research from the supply-based perspective increasingly has relied on managerial cognitions to understand competitive market structures (e.g., Porac and Thomas, 1990). With this approach, one would ask managers from all firms in an industry to define who their competitors are. Nonetheless, empirical research on the supply-based perspective shows remarkable consistency in the results across primary, secondary, and managerial cognitive data (Ketchen *et al*., 1997).

In contrast, demand-based perspectives rely on information obtained directly from consumers. Building on the premise that competitive battles are fought in the minds and hearts of consumers, the main thrust of this research claims that if consumers consider two firms (brands) to be competing, the firms are competitors. The sources of information for the two perspectives are actually complementary and, if used in tandem, could offer managers the greatest benefits. Consider a hypothetical example. Assume that Tata Motors of India decides to enter the U.S. market and position its product relative to the top Japanese firms in the market, Honda and Toyota. At the time of Tata's market entry, the two perspectives are likely to exhibit the following:

1. The supply-side perspective would likely show that (a) due to the initial small scale of operations of Tata Motors in the United States, Tata does not belong to the same strategic group as the Japanese firms and thus does not compete with the Japanese firms, and (b) according to managerial perceptual data, managers of Tata consider the Japanese firms to be their competitors but the Japanese firms do not consider Tata to be their competitor (thereby exhibiting competitive asymmetry).
2. From the demand-side perspective, consumers would unlikely see Tata as competing with Honda and Toyota; thus, data from consumers would show that the firms do not compete. That is, although the two approaches show that Tata Motors does not compete with the Japanese firms, managerial cognition data would indicate that Tata Motors perceives that it does.

Now if Tata Motors fails, the Japanese do not have to worry about it. However, if Tata Motors begins to establish itself in the U.S. marketplace, consumer data would show that consumers are co-considering Tata Motors and the Japanese firms, even though the scale of operations for Tata Motors is smaller than that of the Japanese firms. Therefore, from a demand-based perspective, the firms would be competitors; from a supply perspective, the signal is mixed in that the scale of operations for the firms is very different and thus they are not competing, but managerial cognition data might reveal that the managers see the firms as competitors. This illustration vividly demonstrates the shortfalls of both perspectives and the benefits of viewing the perspectives as complementary.

Finally, the most pertinent issue related to our research relates to ascertaining asymmetric competitive market structures. We believe that the demand perspective has a slight edge over the supply perspective in this context. From a supply perspective, if one uses firm-level data, it becomes relatively difficult to discern competitive asymmetries due to the aggregate nature of the data.[1] For example, a niche player may target the high market share firm, and the high market share firm may ignore the niche player (a possibility of asymmetric competition). However, because the scale of operations and in turn the expenditures on advertisements, promotions, and other competitive tools is likely to differ across the two firms, aggregate data devoid of an in-depth qualitative analysis (which is difficult to do on a large scale) has difficulty pointing to competitive asymmetries. It is possible to gain some insight about what managers are trying to do from the analysis of managerial cognitions and firm communications, but whether these strategies are effective is difficult to fathom solely from managerial cognitions and firm communications. (Note that it is often appropriate for large firms to ignore small firms; thus, every instance of a small firm targeting a large firm as a competitor need not be seen as a case of asymmetric competition.) From a demand perspective, if consumers consider the offering of Firm A as substitute for the offering of Firm B but do not consider the offering of Firm B a substitute for the offering of Firm A, it becomes possible to discern asymmetric competition. Thus, timely data from consumers can be used to uncover asymmetric competitive market structures which emphasizes the importance of the demand perspective for this research endeavor. However, as we stated previously, the proposed

[1] Note that we do not suggest that it is not possible to discern competitive asymmetry from firm-level data but as some information might be lost while aggregating, thereby making it relatively more difficult to discern competitive asymmetries.

spatial methodology to be introduced shortly can be employed effectively from appropriate data collected from either the demand or the supply side.

Choice sets and market structure

The empirical part of our research focuses on developing a new statistical methodology to identify competitive asymmetries using a demand-based perspective. In related literature, researchers (1) explicitly specify asymmetries in terms of the structure uncovered in their data (e.g., DeSarbo and Manrai, 1992; Ramaswamy and DeSarbo, 1990); (2) use posterior calculations for asymmetry indices, such as clout and vulnerability (e.g., Bronnenberg and Vanhonacker, 1996; Bucklin and Srinivasan, 1991); and/or (3) demonstrate asymmetry by showing the differences in the influence of two brands on each other (e.g., Allenby and Rossi, 1991; Blattberg and Wisniewski, 1989). We add to this emerging body of research by developing a new spatial methodology that utilizes consumer choice sets to assess the extent of asymmetric competition. On the basis of Day *et al.*'s (1979) notion that the 'relevant set of products' from a consumer perspective represents competitive market structures, we suggest that the relevant set may vary from one consumer to another. Thus, from a demand perspective, it becomes possible to discern the relevant set of products, or what is popularly referred to as the choice set in consumer research (e.g., Shocker *et al.*, 1991; Urban, Hulland, and Weinberg, 1993), and construct market structures for each consumer or segment or market. These choice sets can be used to uncover competitive asymmetry and, given that consumer data are relatively easier to collect, this approach offers a viable means to ascertain asymmetric competitive market structures.

To reduce decision complexity, consumers often use a phased or a sequential decision-making process in which they first form a down-sized choice set based on non-compensatory rules, and then resort to extensive compensatory evaluation of the brands in the choice set (e.g., Shocker *et al.*, 1991; Urban *et al.*, 1993). Thus, brands in the choice set are salient and accessible to consumers, and the choice among these considered brands is more active and involved (e.g., Lehmann and Pan, 1994; Nedungadi, 1990). The size and composition of the choice sets depend on various consumer (e.g., consumer knowledge; Alba and Hutchinson, 1987), brand (e.g., brand heterogeneity; Grewal, Cline, and Davies, 2003), and contextual (e.g., usage situation; Hauser and Wernerfelt, 1990) factors. The likelihood of a brand entering the choice set usually depends on trade-offs between consideration costs and benefits, and choice sets contain information about consumer preferences for competing brands (Cooper and Inoue, 1996; Roberts and Lattin, 1991).

The case for using choice sets to depict competitive market structure is rather intuitive. In essence, non-empty decision sets enumerate a series of competitive brands that concurrently co-satisfy some internal set of consumer needs. As discussed by DeSarbo and Jedidi (1995), such cognitive decision sets categorize competitive brands into acceptable and non-acceptable groups; such pick-any types of binary data have been the focus of several psychometric MDS procedures for depicting competitive market structures (e.g., DeSarbo and Cho, 1989; DeSarbo and Hoffman, 1987; Jedidi and DeSarbo, 1991). In addition, Cooper and Inoue (1996) suggest that choice sets contain information about consumer preferences for competing brands and thus represent an appropriate means for uncovering market structures. Therefore, we employ choice sets to uncover asymmetric competition and market structure.

ASYMMETRIC COMPETITIVE MAPPING

The proposed MDS model

The objective of our proposed MDS model is to provide a simple, visual, firm- or brand-specific (depending on the unit of analysis) display of the competitive market structure faced by each particular firm/brand (hereafter brand) that accounts for competitive asymmetry. In essence, we formulate a new MDS model that estimates a separate 'map' of the competitive landscape for *each* brand in the analysis using demand aspects of the customer base that each firm serves. To develop the brand competitive map, we condition the model on consumers' evoked choice sets (e.g., Cooper and Inoue, 1996; DeSarbo and Hoffman, 1987, DeSarbo and Jedidi, 1995; Jedidi and DeSarbo, 1991). This newly developed spatial methodology can be employed at either the aggregate market level or a designated (known) market segment level. In the Discussion section, we also reveal how the procedure can be generalized to situations in which it can simultaneously uncover unknown market segments through a latent structure formulation. Furthermore, the proposed methodology can be used for any particular competitive scenario within any specified industry.

Specifically, we use the following notation:

$$
\begin{aligned}
i &= 1, \ldots, N \text{ consumers,}\\
j, k &= 1, \ldots, B \text{ brands,}\\
t &= 1, \ldots, T \text{ dimensions,}\\
r &= 1, \ldots, R \text{ replications(time, situations, purchase occasions, etc.)}\\
Y_{ijr} &= \left(\begin{array}{l} 1 \text{ if consumer } i \text{ considers/choosesfirm/ brand } j \text{ in replication } r;\\ 0 \text{ otherwise.} \end{array} \right.
\end{aligned}
$$

Consistent with Nakatani (1972), Takane (1981), and Takane and Carroll (1981), we define an additive latent distance variable:

$$D_{ijkr}^{(j)} = \lambda_{jk}^{(j)} + e_{ijkr}^{(j)} \tag{1}$$

where

$$
\begin{aligned}
\lambda_{jk}^{(j)} &= \sqrt{\sum_{t=1}^{T} (X_{jt}^{(j)} - X_{kt}^{(j)})^2} \\
&\quad \text{Euclidean distance} \qquad (2)\\
X_{kt}^{(j)} &= \text{the } t\text{th coordinate for brand } k \text{ in the map for referent brand } j; \text{ and}\\
e_{ijkr}^{(j)} &= error\ iid\ N(0, \sigma_j^2), \forall, i, r
\end{aligned}
$$

such that

$$P(Y_{ikr} = 1 | Y_{ijr} = 1) = P(D_{ijkr}^{(j)} \leq c_j) \tag{3}$$

and

$$P(Y_{ikr} = 0 | Y_{ijr} = 1) = P(D_{ijkr}^{(j)} > c_j) \tag{4}$$

where $c_j =$ a threshold distance for brands in the map for referent brand j.

Thus, we construct a separate competitive map for each (referent) brand, conditional on that referent brand being selected in the choice set. The focus is on other brands that are jointly selected for the same choice sets. We posit that the composition of such cognitive decision sets is such that brands within a threshold competitive distance from the referent brand are jointly probabilistically considered with the referent brand (j) and are thus represented as active competitors.

Now, given a sample of observations Y, we form a conditional likelihood function:

$$L = \prod_{i=1}^{N} \prod_{\substack{j=1 \\ Y_{ijr}=1}}^{B} \prod_{r=1}^{R} \prod_{k \neq j}^{B} P(Y_{ikr} = 1 | Y_{ijr} = 1)^{M_{ijkr}} \times P(Y_{ikr} = 0 | Y_{ijr} = 1)^{1-M_{ijkr}} \tag{5}$$

where

$$M_{ijkr} = \left(\begin{array}{l} 1 \text{ if } Y_{ijr} = Y_{ikr} = 1 \\ 0 \text{ else } Y_{ijr} = 1, Y_{ikr} = 0 \end{array} \right.$$

We can therefore rewrite the conditional likelihood function as

$$L = \prod_{i=1}^{N} \prod_{\substack{j=1 \\ Y_{ijr}=1}}^{B} \prod_{r=1}^{R} \prod_{k \neq j}^{B} P(D_{ijkr}^{(j)} \leq c_j)^{M_{ijkr}} \times P(D_{ijkr}^{(j)} > c_j)^{1-M_{ijkr}} \tag{6}$$

or the corresponding conditional log-likelihood function as

$$LnL = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ Y_{ijr}=1}}^{B} \sum_{r=1}^{R} \sum_{k \neq j}^{B} \Big[M_{ijkr} \ln P(D_{ijkr}^{(j)} \leq c_j) + (1 - M_{ijkr}) \ln P(D_{ijkr}^{(j)} > c_j) \Big]. \tag{7}$$

Now,

$$
\begin{aligned}
P(D_{ijkr}^{(j)} \leq c_j) &= P(\lambda_{jk}^{(j)} + e_{ijkr}^{(j)} \leq c_j) && (8)\\
&= P(e_{ijkr}^{(j)} \leq c_j - \lambda_{jk}^{(j)}) && (9)\\
&= \Phi \left(\frac{c_j - \sqrt{\sum_{t=1}^{T} (X_{jt}^{(j)} - X_{kt}^{(j)})^2}}{\sigma_j} \right) && (10)\\
&\overset{\text{WLOG}}{=} \Phi \left(c_j - \sqrt{\sum_{t=1}^{T} (X_{jt}^{(j)} - X_{kt}^{(j)})^2} \right), && (11)
\end{aligned}
$$

and thus

$$P(D_{ijkr}^{(j)} > c_j) = 1 - \Phi\left(c_j - \sqrt{\sum_{t=1}^{T}(X_{jt}^{(j)} - X_{kt}^{(j)})^2}\right) \quad (12)$$

Therefore, given the binary consideration data $Y = ((Y_{ijr}))$ and a value of T (number of dimensions), we estimate the brand coordinates $\underset{\sim}{X}^{(j)}$, $c_j \forall j = 1, \ldots, B$ (the brand configurations and brand-specific threshold coefficients) to maximize *Ln L*. We use a conjugate, gradient-based, nonlinear optimizer for this purpose.

Several estimation issues arise with respect to the specification in Equations 1–12. First, there are a rather large number of parameters to estimate given the need for B separate brand maps. Second, within each derived map, the between-brand distances are indeterminate or unidentifiable. That is, only distances from the referent brand are estimable in a reduced dimensionality. Third, there is a scalar indeterminacy with respect to the threshold coefficients and the separate brand map coordinates. To alleviate these difficulties, we employ the following reparameterization:

$$X_{kt}^{(j)} = \mathrm{W}_{jk} X_{kt}^{(*)} \quad (13)$$

where $X_{kt}^{(*)}$ is a specified average or pooled configuration of brands, and W_{jk} is an estimated set of brand-specific transformation coefficients, for which $\mathrm{W}_{\mathrm{jj}} = 1$ for all $j = 1, \ldots,$ B brands. In essence, Equation 13 represents a type of external analysis (akin to PREFMAP1), where $\mathbf{X}^*$ can be specified *a priori*, generated internally through a singular value decomposition (SVD) analysis (cf. Krzanowski, 2000) akin to principal components analysis of the preprocessed $\mathbf{Y'Y}$ matrix (as in PREFMAP2), or estimated from an allied data set associated with the particular application (e.g., brand attribute data). This analysis aids in reducing the total number of parameters to be estimated in most applications and resolves the problem of indeterminate brand distances within each map.

It is also important to note here that the B derived maps are separable, computationally speaking. Some of the data are employed multiple times in the *complete* sample likelihood expression, since $M_{ijkr} = 1$ implies $M_{ikjr} = 1$. However, because there are no overlapping sets of parameters to be estimated across referent brands, the data are counted only once within a referent brand map. Therefore, the maps can be estimated one at a time or jointly. In joint estimation, the data use replication affects the degrees of freedom calculations in estimation and subsequent model comparison tests, which means we should only count usable data once in the derivation of such maps in degrees of freedom calculations. Note that the effective number of independent total observations here is difficult to reduce to a simple algebraic expression because $M_{ijkr} = 1$ implies $M_{ikjr} = 1$, and O therefore must be conditioned for multiple uses of these observations. As such, a very conservative approach, and one adopted here, is to define $O = N$, the sample size, assuming non-sparse data in each of the rows of $\mathbf{Y}$. The general expression for the number of free parameters estimated given Equation 13 is

$$\mathrm{P} = \left((B)T + B(B-1) + B - \frac{T(T-1)}{2}\right) \quad (14)$$

Thus, we obtain B different maps, one for each brand as that serves as a referent, where the competitive choice set is delineated for each referent brand. This framework accommodates the competitive asymmetry in the market place since in general:

$$P(Y_{ijr} = 1 | Y_{ikr} = 1) \neq P(Y_{ikr} = 1 | Y_{ijr} = 1) \quad (15)$$

More specifically, the exact relationship between the two conditional probabilities is

$$P(Y_{ikr} = 1 | Y_{ijr} = 1) = P(Y_{ijr} = 1 | Y_{ikr} = 1) \times P(Y_{ikr} = 1) / P(Y_{ijr} = 1) \quad (16)$$

which are equal if and only if $P(Y_{ikr} = 1) = P(Y_{ijr} = 1)$. Thus, brand A may be within referent B's threshold region for choice but not necessarily vice versa.

Thus, for $T = 2$ dimensions, one can obtain spatial representations for each $j = 1, \ldots,$ B brands, as illustrated in Figure 1, for one hypothetical referent brand J map. Figure 1 depicts an illustrative competitive map derived from the proposed methodology for a hypothetical referent brand J, here estimated in the map (large bold **J**) located near the origin of the two-dimensional space. In this illustration, we assume 10 brands labeled A–J. The proposed methodology therefore would

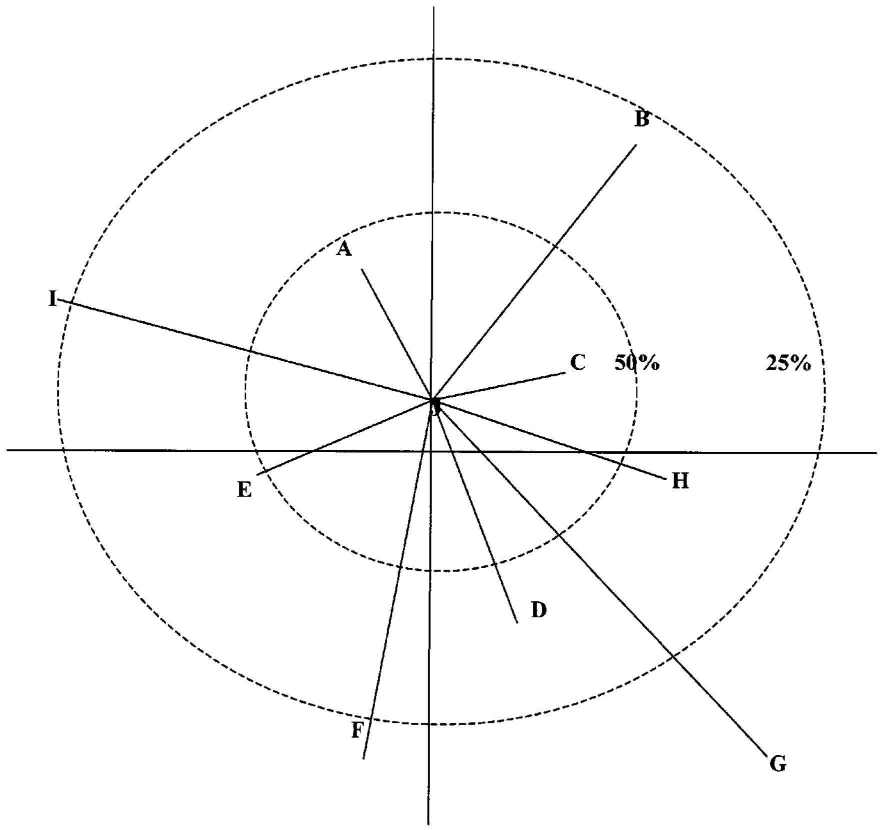

Figure 1. Illustrative brand map for referent brand J

simultaneously estimate 10 maps, one for each brand as referent. As explicitly shown in Figure 1, the length of the vectors connecting each of the other $B - 1 = 9$ brands to the referent brand J signifies the competitive distance of each brand from referent brand J. That is, the length of this vector is inversely proportionate to the probability that each other brand will be in the consideration set with brand J. The radius of the inner dashed circle in $T = 2$ dimensions indicates the threshold value c_J, which defines the model-predicted choice set boundaries (at least 50% conditional consideration probability for all brands within this region). In a similar fashion, one can construct circular probability contours of consideration set inclusion as a set of concurrent, varying radii circles around J, as has been done in the illustration to denote the 25 percent consideration probability boundary (at least 25% conditional consideration probability for all brands within this region). Thus, in Figure 1, the spatial model predicts brands A and C to be jointly considered (i.e., competitive) when J is considered, whereas the remaining brands are not (at least 50% of the time). Note in $T = 3$ dimensions, these competitive contours are spheres.

Model selection

Consistent with the literature on stochastic MDS procedures estimated via maximum likelihood with binary data (e.g., DeSarbo and Cho, 1989; DeSarbo and Hoffman, 1986, 1987; DeSarbo, Libby, and Jedidi, 1994; Jedidi and DeSarbo, 1991), we use information-based heuristics to select the most parsimonious model solution fit by this procedure. In particular, we inspect AIC, BIC, and CAIC heuristics calculated as follows:

$$\mathrm{AIC} = -2\mathrm{Ln}L^* + 2P \quad (17)$$

$$\mathrm{BIC} = -2\mathrm{Ln}L^* + P\mathrm{Ln}(O);\text{ and} \quad (18)$$

$$\mathrm{CAIC} = -2\mathrm{Ln}L^* + P(\mathrm{Ln}(O) + 1) \quad (19)$$

where P is the number of independent parameters to be estimated and O is the number of independent observations. We then select the model solution that has minimal value with respect to these criteria. Such information-theoretic criteria are appropriate for comparing both nested and non-nested models with the same likelihood function form and model and have been justified for model comparison testing in a variety of ways (for detailed theoretical derivations and discussions, see Bozdogan, 1987). The first term reflects a lack of fit, whereas the second term is the penalty component that denotes the use of additional parameters. Many authors (e.g., Bozdogan, 1987) have noted the tendency of the AIC to favor over-parameterized models and have recommended the BIC and CAIC as more conservative heuristics. In the present MDS context, we employ these heuristics to perform tests of the equality restrictions for subsets of parameters, external analyses when **X** may have been derived elsewhere, $X_{kt}^{(j)} = X_{kt}$ (i.e., one common space), and other parameter restriction options relevant to a particular application. In particular, we employ these model selection heuristics to test symmetric vs. asymmetric market structures.

Program options

There are several alternative model specifications. For example, to reduce the number of parameters to estimate, we could merely consider the symmetric version of the model with one common space for all J maps with $X_{kt}^{(j)} = X_{kt}$ and assume all $W_{jk} = 1$ with free threshold coefficients. Assuming *a priori* that theoretically meaningful values of parameters were available from previous studies, we could also fix the configuration **X** at some value $\mathbf{X}^*$ and estimate symmetric or asymmetric models with free threshold values and/or weights **W**. Again, the various information heuristics in Equations 17–19 can be employed to test for parsimonious model selection for subsets of competing model solutions, akin to most other likelihood-based MDS procedures.

APPLICATION I: LUXURY AUTOMOBILES

Study background

A major U.S. automobile manufacturer sponsored research to conduct personal interviews with N = 240 consumers who stated that they intended to purchase a luxury automobile within the next 6 months. These customers were demographically screened to represent the target market segment of interest. The study was conducted in various automobile clinics occurring at different geographical locations in the United States. One section of the questionnaire asked respondents to check off from a list of 10 luxury cars, specified *a priori* by this manufacturer and thought to compete in the same market segment at that time (based on prior research), which brands they would consider purchasing as a replacement vehicle after recalling their perceptions of the expected benefits and costs of each brand. Then respondents were asked to use a 10-point scale to indicate the intensity of their purchase consideration for the vehicles initially checked as in their consideration sets. The 10 nameplates tested were (firms that manufacture them in parentheses): Lincoln Continental (Ford), Cadillac Seville (GM), Buick Riviera (GM), Oldsmobile 98 (GM), Lincoln Town Car (Ford), Mercedes 300E (Daimler/Chrysler), BMW 325i (BMW), Volvo 740 (Ford), Jaguar XJ6 (Ford), and Acura Legend (Honda). The vast majority of respondents' elicited choice sets were in the range of two to six automobiles from the list of 10. See DeSarbo and Jedidi (1995) for further study details.

In Table 1, we present the joint probabilities ($P(Y_{ij} = 1)$ and $P(Y_{ik} = 1)$) of co-considering brands $(i,\ j)$ in portion (a) and the computed matrix of conditional probabilities ($P(Y_{ij} = 1)|$ $P(Y_{ik} = 1)$) or 'cohits' (i.e., the $(i,\ j)$ entry designates the percentage of the column brand selected in the same consideration set as the row brand), in portion (b). In other words, Table 1(a) indicates the probability of jointly considering brands i and j together, whereas Table 1(b) indicates the probability, given that the row brand was in a consideration set, that the column brand was also selected. The first matrix in (a) is symmetric, but the conditional probabilities in (b) are asymmetric. The main diagonals of the matrix in Table 1(a) render the probability that the particular brand was considered and relates to the brand's share of these consumers' consideration sets. As shown in the main diagonals of Table 1(a), only the Lincoln Town Car appears in the choice sets of over half of the respondents, followed in popularity by the Acura Legend and Lincoln Continental. The BMW 325i was the least considered luxury car on the list (considered by only 44 of 240 respondents).

Table 1(a). Matrix of joint probabilities

Cont'l	Seville	Riviera	Olds98	Twncar	Merc	BMW	Volvo	Jag	Lgnd
0.425	0.183	0.121	0.163	0.300	0.133	0.050	0.108	0.096	0.171
0.183	0.392	0.146	0.171	0.238	0.142	0.050	0.096	0.088	0.121
0.121	0.146	0.317	0.175	0.242	0.067	0.025	0.071	0.033	0.117
0.163	0.171	0.175	0.371	0.242	0.083	0.038	0.096	0.029	0.121
0.300	0.238	0.242	0.242	0.650	0.221	0.104	0.213	0.129	0.246
0.133	0.142	0.067	0.083	0.221	0.388	0.129	0.188	0.129	0.217
0.050	0.050	0.025	0.038	0.104	0.129	0.183	0.133	0.050	0.133
0.108	0.096	0.071	0.096	0.213	0.188	0.133	0.338	0.083	0.204
0.096	0.088	0.033	0.029	0.129	0.129	0.050	0.083	0.217	0.117
0.171	0.121	0.117	0.121	0.246	0.217	0.133	0.204	0.117	0.458

Table 1(b). Matrix of conditional probabilities

Cont'l	Seville	Riviera	Olds98	Twncar	Merc	BMW	Volvo	Jag	Lgnd
1.000	0.431	0.284	0.382	0.706	0.314	0.118	0.255	0.225	0.402
0.468	1.000	0.372	0.436	0.606	0.362	0.128	0.245	0.223	0.309
0.382	0.461	1.000	0.553	0.763	0.211	0.079	0.224	0.105	0.368
0.438	0.461	0.472	1.000	0.652	0.225	0.101	0.258	0.079	0.326
0.462	0.365	0.372	0.372	1.000	0.340	0.160	0.327	0.199	0.378
0.344	0.366	0.172	0.215	0.570	1.000	0.333	0.484	0.333	0.559
0.273	0.273	0.136	0.205	0.568	0.705	1.000	0.727	0.273	0.727
0.321	0.284	0.210	0.284	0.630	0.556	0.395	1.000	0.247	0.605
0.442	0.404	0.154	0.135	0.596	0.596	0.231	0.385	1.000	0.538
0.373	0.234	0.255	0.264	0.536	0.473	0.291	0.445	0.255	1.000
Vincibility									
0.346	0.350	0.349	0.335	0.330	0.375	0.432	0.392	0.387	0.351
Potency									
0.389	0.368	0.270	0.316	0.625	0.420	0.204	0.372	0.215	0.468

Focusing on Table 1(b), by comparing entry (i, j) with entry (j, i), we obtain a quick assessment of the degree and nature of this asymmetry. For example, the Riviera (i) Town Car (j) entry of 0.763 is far larger than the Town Car (j) Riviera (i) entry of 0.372, thereby suggesting that the Town Car is co-selected in many more consideration sets with Riviera than is the Riviera with the Town Car. We can get a preliminary summary of this asymmetric row vs. column phenomenon by computing simple averages of the rows and columns (ignoring the main diagonal element). Akin to Kamakura and Russell's (1989) notions of 'clout' and 'vulnerability' when dealing with summaries of calculated marketing mix elasticities, we compute these averages, also presented in Table 1(b), and label them as *vincibility* (row averages) and *potency* (column averages). Note the pronounced differences in the corresponding row vs. column averages for the Town Car, BMW, and Jaguar, which indicate substantial competitive asymmetry.

Traditional MDS results

In Figure 2, we present the traditional ALSCAL MDS (available from SPSS for Windows software) results for $T = 2$ dimensions ($T = 2$ was determined by scree plot as the most parsimonious for $T = 1, 2, 3, 4$) derived from dissimilarities computed over the raw choice set data. (The presence of two dimensions was also verified by our internal SVD analysis (cf. Krzanowski, 2000) of $\mathbf{Y'Y}$ within our computer program. In addition, this solution was nearly identical, after rotation, to the ALSCAL T = 2 solution derived from an analysis of the consideration intensity data collected from these same consumers, which could have been used in the analyses to follow.) The horizontal axis separates imported luxury cars (left) from domestic luxury cars (right). The vertical axis appears to separate GM luxury cars (top) from Ford luxury cars (bottom), with the imports aggregated in the middle. This figure implies that foreign luxury cars

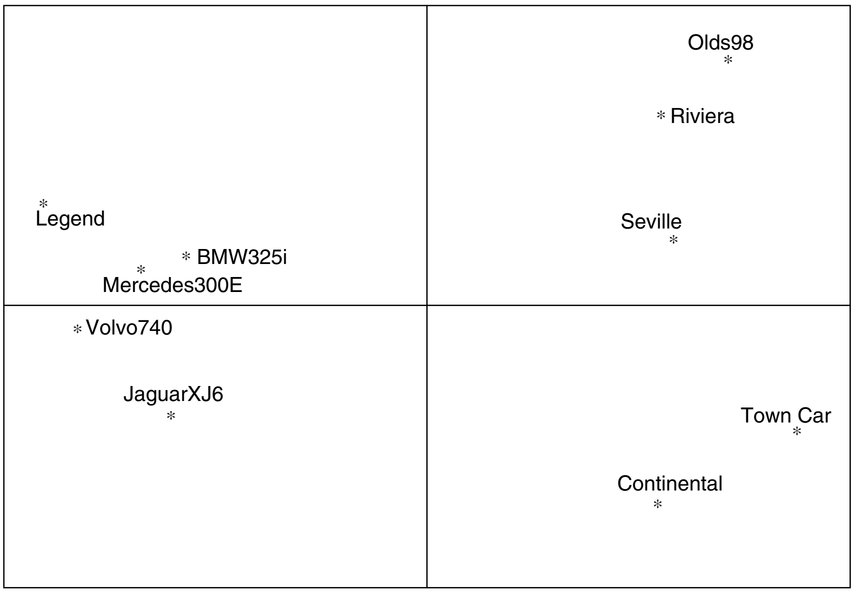

Figure 2. Aggregate market map from ALSCAL for luxury automobiles

appear to be jointly considered, seeing how tightly clustered they are together, in direct contrast with the domestic cars, for which such grouping tends to be oriented around the manufacturer (Ford vs. GM) and thereby implies considerable potential cannibalism. From a positioning perspective, these consumers also appear to find domestic brands more distinctive from one another than the imports.

The proposed MDS model results

Our proposed asymmetric stochastic MDS model was estimated for $T = 2$ dimensions using the derived SPSS map presented in Figure 2 as $\mathbf{X}^*$ in an external analysis (we also do this to test the traditional symmetric solution vs. this asymmetric one). In Table 2, we present the associated information heuristics associated with this solution. We also compared this solution with a much simpler one (2a in Table 2) for which we assume the aggregate SPSS map is fixed for all 10 maps with estimated variable threshold values but weights fixed equal to 1.0 to simulate the adaptation of the aggregate SPSS map to represent symmetry in the data set. As we show in Table 2, this latter symmetric solution is clearly rejected in favor of the asymmetric solution ascertained by *all* the information heuristics. In addition, we computed the predicted aggregate conditional probabilities for each of the two solutions, as well as root mean square errors (RMSE) for the predictions from each vs. the actual conditional probabilities presented in Table 1(b). The RMSE for the symmetric solution was 0.226 compared with 0.024 for the asymmetric solution, a ratio of almost 10 to 1 for these error rates.

In Figures 3–5, we present the 10 estimated brand-specific maps organized by manufacturer (Ford, GM, and Imports). In each case, the circular

Table 2. Luxury automobile information heuristics

Number of dimensions	Number of parameters	Ln *L*	AIC	BIC[a]	CAIC[a]
2*	119	−4856.04	9950.09	10364.28	10438.28
2a**	29	−6611.28	13280.57	13381.51	13410.57

* Denotes asymmetric solution
** Denotes symmetric solution
[a] Calculated conservatively with O = N

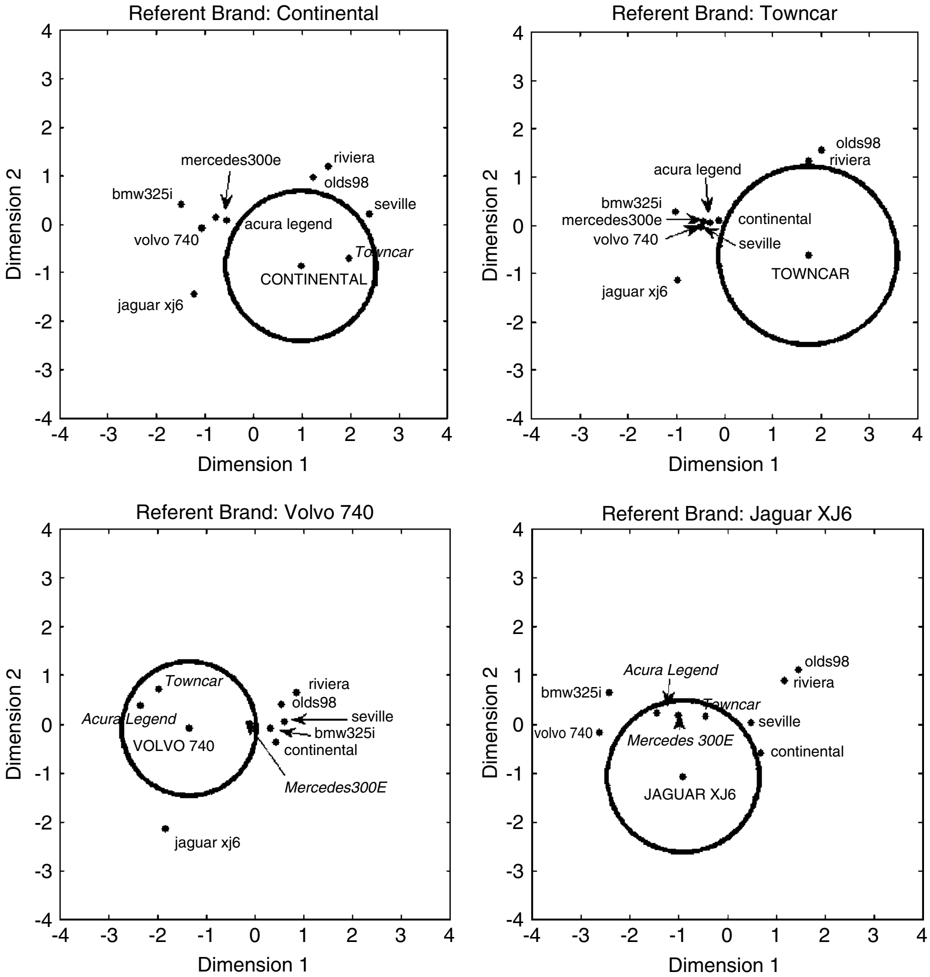

Figure 3. Brand-specific maps for Ford brands

area surrounding the referent brand denotes the 50 percent consideration threshold region. Brands within the threshold region are predicted to be probabilistically co-considered with the referent brand. That is, the model predicts those brands within the inner threshold region will be the most competitive with each of the referent brands. For our discussions of each figure, in which we investigate the brand-specific dynamics and asymmetries, we use different font sizes in the maps to denote the competitive status of the brands: the referent brand is labeled with the largest bold font located in the center of the circular consideration regions. The brands within these 50 percent consideration regions are denoted with the italicized next largest size font. Finally, all brands located outside the 50 percent consideration region are designated with lower case, smallest size font (we ignore the 25% region to avoid clutter in these derived spaces).

In Figure 3, we present the conditional brand maps for the four Ford brands: Lincoln Continental, Lincoln Town Car, Jaguar XJ6, and Volvo 740. The Lincoln Continental's major competition arises from its sister brand, the Lincoln Town Car, a problem of potential cannibalism for Ford. The Cadillac Seville and Acura Legend appear as secondary competitors. The Lincoln Town Car, in contrast, appears wonderfully positioned because it has no other brands within its inner threshold region, though the Riviera and Continental are located just outside the boundary. We see a different situation with respect to the two Ford import brands. For the Volvo 740, Town Car, Legend, and Mercedes are all within its inner threshold region, indicating stiff competition. Given the

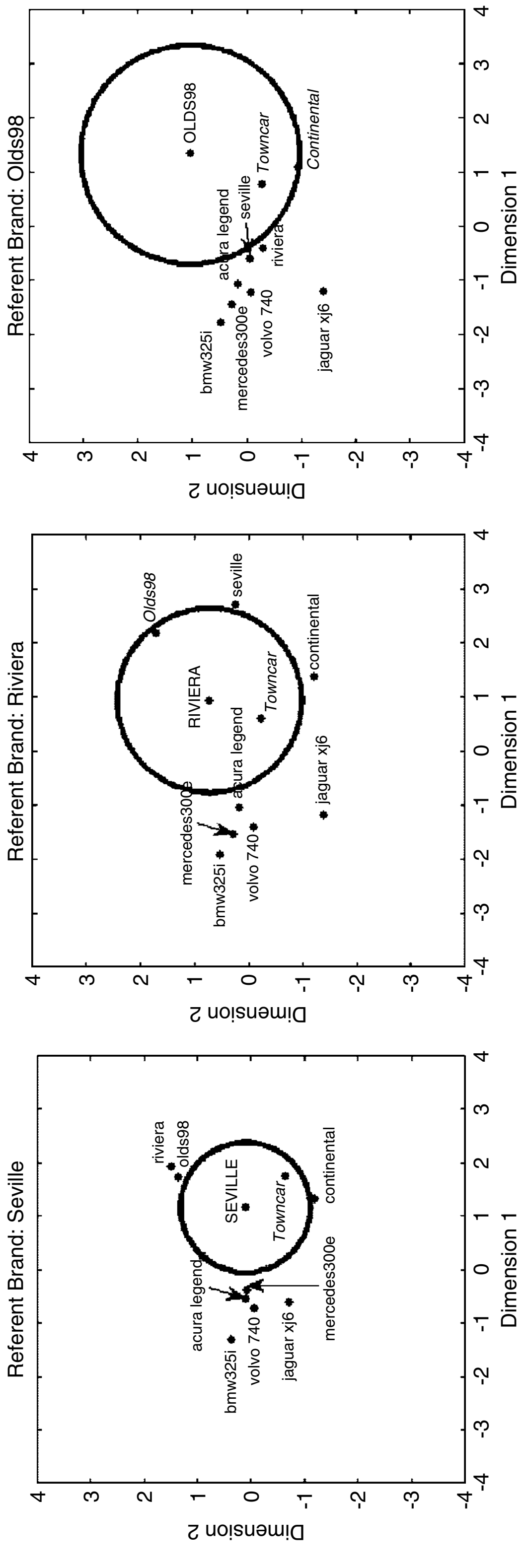

Figure 4. Brand-specific maps for GM brands

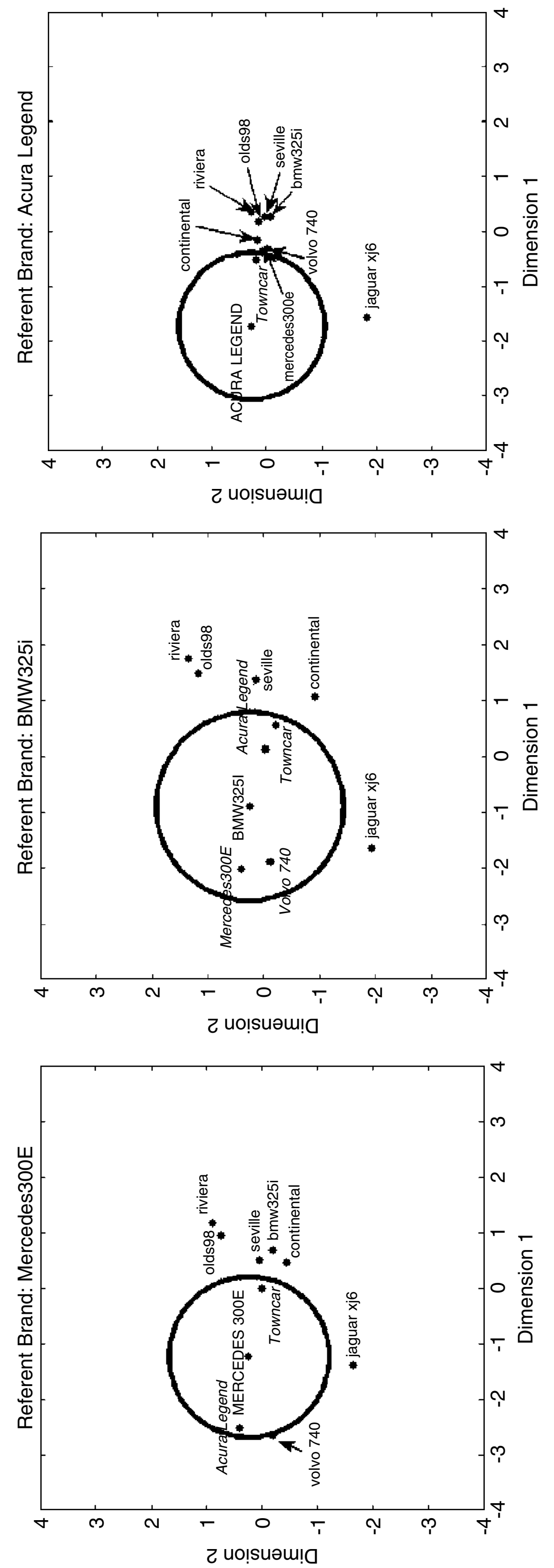

Figure 5. Brand-specific maps for imported brands

unique positioning of Volvo's advertising (safety), this finding is somewhat surprising. The sporty Jaguar XJ6 has a similar competitive profile with these same three brands as primary competitors.

In Figure 4, we present the conditional maps for the three GM brands: the Cadillac Seville, Buick Riviera, and Oldsmobile 98. While all three GM brands appear nicely protected from competitive threats from the imports, the maps identify problems in their domestic competition. Specifically, the Seville's main competition comes from the Town Car, with secondary threats from the Continental and Olds98. The Buick Riviera is most threatened by the Town Car and the Olds98, with secondary competition from Seville. Finally, although the Town Car is the only inner threshold competitive brand for the Olds98, the other three domestic brands are right near the inner circle boundary. Thus, GM has potential cannibalism problems among its three brands.

In Figure 5, we present the conditional brand maps estimated for the three remaining imported brands from different manufacturers: the Mercedes 300E, BMW 325i, and Acura Legend. Mercedes' major competitive threats come from the Town Car and Legend, with secondary threats from Volvo. BMW faces the strongest competition from Mercedes, Volvo, the Legend, and the Town Car. Of the group, Acura Legend appears to be in the best position, given that only the Town Car is located within its inner threshold, with secondary competition from Mercedes and Volvo.

Notice how the derived aggregate ALSCAL map in Figure 2 masks much of this brand-specific asymmetric competition. Whereas threshold regions are not defined in such traditional MDS spaces, brand distances are. The operating assumption is that brands closest to a given brand will be the most competitive. Yet, as shown and discussed in Figures 3–5, different asymmetric scenarios are obtained by the application of our proposed MDS methodology, scenarios that do not follow the simplistic implications of the aggregate MDS-derived map alone.

APPLICATION II: PORTABLE TELEPHONES

Study description

A major U.S. telecommunications firm sponsored a research project to gain a better understanding of consumer preferences and intended choices for various brands of portable telephones and their various features, as well as to find potential markets for new offerings. The study was conducted in 1984 when the product class was somewhat new, and involved a total of 499 personal interviews at four geographically disperse, high-traffic malls. Potential respondents were demographically screened on the basis of information about their family income, size of family, and head of household's age, education, and occupation to represent the target market segment. Eligible respondents were escorted to a completely enclosed interviewing area where 12 actual potable telephone products/brands were exhibited. Respondents were read a description of each brand by the interviewer who then demonstrated how each brand was to be used. Respondents were asked whether they would consider buying each of the 12 devices within the next 6 months ($0 =$ would not buy; $1 =$ would buy). Because of the proprietary nature of the research, the letters A–L are used to identify the 12 brands. This product class is one in which multiple brand purchases are common (cf. DeSarbo and Hoffman, 1987; DeSarbo and Rao, 1986). In Table 3, we present several brand features/attributes that differentiate these brands (cf. DeSarbo and Green, 1984).

As we did for Application I, in Table 4 we present the symmetric joint probabilities ($P(Y_{ij} = 1)$ and $P(Y_{ij} = 1)$) of co-considering brands (i, j) and the asymmetric computed matrix of conditional probabilities ($P(Y_{ij} = 1)|P(Y_{ik} = 1)$) or 'cohits.' The main diagonals of the matrix in Table 4(a) indicate the probability that the particular brand was considered (i.e., the brands' consideration shares). Although no brand was selected more than 50 percent of the time, there seems to be a clear preference for brands E, I, C, and L, which provide more features (i.e., send and receive capability, higher range, and repertory dialing/memory) than the lower-priced brands A, B, and H. Focusing on Table 4(b), by comparing entry (i, j) with entry (j, i), we can obtain an assessment of the degree and nature of the asymmetry in the data. For example, the (A, E) entry in Table 4(b) far exceeds the (E, A) entry (more than three times in magnitude). We also calculate our vincibility and potency indices for each of the 12 brands, which clearly indicate the asymmetry in competitive standings among the brands studied. In particular, brands A, B, H, and K have vincibility indices nearly double

Table 3. Brand attribute/feature data

Brand	Transmit (1)	Memory (2)	Range (3)	Price (4)	Speakerphone (5)	Privacy (6)	Style (7)
A	Receive	None	300′	$119.95	None	None	Cradle
B	Receive	None	300′	$119.95	None	None	Cradle
C	Send & Receive	1#	300′	$219.95	None	None	Cradle
D	Send & Receive	1#	300′	$299.95	None	None	Cradle
E	Send & Receive	1#	300′	$199.95	None	None	Cradle
F	Send & Receive	1#	300′	$239.95	None	None	Cradle
G	Send & Receive	None	300′	$219.95	None	None	Cradle
H	Send & Receive	None	50′	$99.95	None	None	W-T*
I	Send & Receive	3#	1000′	$299.95	Yes	None	W-T*
J	Send & Receive	1#	300′	$299.95	Yes	None	W-T*
K	Send & Receive	1#	300′	$249.95	None	None	W-T*
L	Send & Receive	12#	1000′	$299.95	None	Yes	W-T*

* W-T denotes a walkie-talkie design.

Table 4. Portable telephone consideration probabilities

(a) Joint probabilities

A	B	C	D	E	F	G	H	I	J	K	L
0.157	0.108	0.080	0.048	0.105	0.051	0.063	0.080	0.057	0.031	0.031	0.066
0.108	0.160	0.077	0.060	0.105	0.057	0.077	0.068	0.060	0.031	0.028	0.068
0.080	0.077	0.396	0.185	0.333	0.217	0.205	0.140	0.197	0.145	0.123	0.191
0.048	0.060	0.185	0.279	0.205	0.188	0.151	0.057	0.179	0.128	0.097	0.145
0.105	0.105	0.333	0.205	0.479	0.254	0.239	0.191	0.239	0.168	0.123	0.194
0.051	0.057	0.217	0.188	0.254	0.308	0.174	0.083	0.174	0.120	0.103	0.154
0.063	0.077	0.205	0.151	0.239	0.174	0.336	0.117	0.174	0.123	0.100	0.151
0.080	0.068	0.140	0.057	0.191	0.083	0.117	0.382	0.128	0.083	0.054	0.117
0.057	0.060	0.197	0.179	0.239	0.174	0.174	0.128	0.462	0.191	0.123	0.231
0.031	0.031	0.145	0.128	0.168	0.120	0.123	0.083	0.191	0.276	0.091	0.128
0.031	0.028	0.123	0.097	0.123	0.103	0.100	0.054	0.123	0.091	0.177	0.128
0.066	0.068	0.191	0.145	0.194	0.154	0.151	0.117	0.231	0.128	0.128	0.405

(b) Conditional probabilities

A	B	C	D	E	F	G	H	I	J	K	L
1.000	0.691	0.509	0.309	0.673	0.327	0.400	0.509	0.364	0.200	0.200	0.418
0.679	1.000	0.482	0.375	0.661	0.357	0.482	0.429	0.375	0.196	0.179	0.429
0.201	0.194	1.000	0.468	0.842	0.547	0.518	0.353	0.496	0.367	0.309	0.482
0.173	0.214	0.663	1.000	0.735	0.673	0.541	0.204	0.643	0.459	0.347	0.520
0.220	0.220	0.696	0.429	1.000	0.530	0.500	0.399	0.500	0.351	0.256	0.405
0.167	0.185	0.704	0.611	0.824	1.000	0.565	0.269	0.565	0.389	0.333	0.500
0.186	0.229	0.610	0.449	0.712	0.517	1.000	0.347	0.517	0.364	0.297	0.449
0.209	0.179	0.366	0.149	0.500	0.216	0.306	1.000	0.336	0.216	0.142	0.306
0.123	0.130	0.426	0.389	0.519	0.377	0.377	0.278	1.000	0.414	0.265	0.500
0.113	0.113	0.526	0.464	0.608	0.433	0.443	0.299	0.691	1.000	0.330	0.464
0.177	0.161	0.694	0.548	0.694	0.581	0.565	0.306	0.694	0.516	1.000	0.726
0.162	0.169	0.472	0.359	0.479	0.380	0.373	0.289	0.570	0.317	0.317	1.000
Vincibility											
0.418	0.422	0.434	0.470	0.410	0.465	0.425	0.266	0.345	0.408	0.515	0.353
Potency											
0.219	0.226	0.559	0.414	0.659	0.449	0.461	0.335	0.523	0.345	0.270	0.473

their respective potency measures, whereas C, E, and I have significantly higher potency indices than vincibility indices, which indicates their strong positioning in the marketplace.

Traditional MDS results

In Figure 6, we present the traditional ALSCAL MDS results for T = 3 dimensions (as determined by scree plot analysis), derived from dissimilarities computed over the raw consideration/intention set data. (Again, the presence of three dimensions was verified by our internal SVD analysis of $\mathbf{Y'Y}$ within our computer program. The derived solution was nearly identical (after rotation) to the ALSCAL T = 3 solution and could have been utilized in the analysis to follow.) To aid interpretations of the derived three dimensions, Table 5 presents the correlations of each dimension with each of the seven portable telephone features presented in Table 3. Correlations in excess of 0.5 in absolute value are shown in bold type to denote those features that relate most to each dimension. The first dimension distinguishes the cradle style from the walkie-talkie style phones (STYLE). The second dimension separates pricier phones with send and receive capability from lower-priced, receive-only phones (PRICE). Finally, the third dimension relates to repertory dialing, range, speakerphone, and privacy attributes (FEATURES).

Table 5. Brand attribute/feature correlations with dimensions

Feature #	Dimension		
	I	II	III
1	0.201	**0.841**	−0.134
2	0.305	0.100	**0.595**
3	0.286	0.154	**0.747**
4	0.048	**0.803**	**0.559**
5	0.476	0.258	0.388
6	0.274	−0.045	**0.506**
7	**0.869**	0.058	0.441

The proposed MDS model results

Our proposed asymmetric stochastic MDS model was estimated for T = 3 dimensions using the derived SPSS map presented in Figure 6 as $\mathbf{X}^*$ in an external analysis (as in the luxury automobile example, we do this to test the fit of the symmetric solution vs. this asymmetric one explicitly). In Table 6, we present the information heuristics associated with this solution. We also compared the solution with a much simpler one (3a in Table 6) in which we assumed the aggregate SPSS map was fixed for all 12 maps—with estimated variable threshold values but weights fixed equal to 1.0—to simulate adapting the aggregate SPSS map to represent only symmetry in this data set. As shown in Table 6, this latter symmetric solution is clearly rejected in favor of the asymmetric solution as ascertained by *all* the information heuristics, as we also noted in the luxury automobile application. In addition, we computed the predicted aggregate conditional probabilities for each of the two solutions, as well as the RMSE for the predictions from each compared with the actual conditional probabilities presented in Table 4(b). The RMSE for the symmetric solution was 0.222 vs. 0.055 for the asymmetric solution, a ratio of more than four to one.

Figure 7 depicts the 12 brand plots (A–L) in the three derived dimensions. Here, the referent brand is labeled as the bold-font largest-sized letter located in the center of the 50 percent consideration sphere. Brands located within the 50 percent consideration sphere are labeled with the next largest font. Finally, brands located outside of the sphere consideration region are labeled in lower case letters. In three dimensions, the competitive boundaries are defined as spheres, each

Table 6. Portable telephone information heuristics

Number of dimensions	Number of parameters	Ln *L*	AIC	BIC[a]	CAIC[a]
3*	177	−9173.53	18701.06	19384.42	19561.42
3a**	45	−12860.47	25810.95	25984.69	26029.69

* Denotes asymmetric solution
** Denotes symmetric solution
[a] Calculated conservatively with O = N

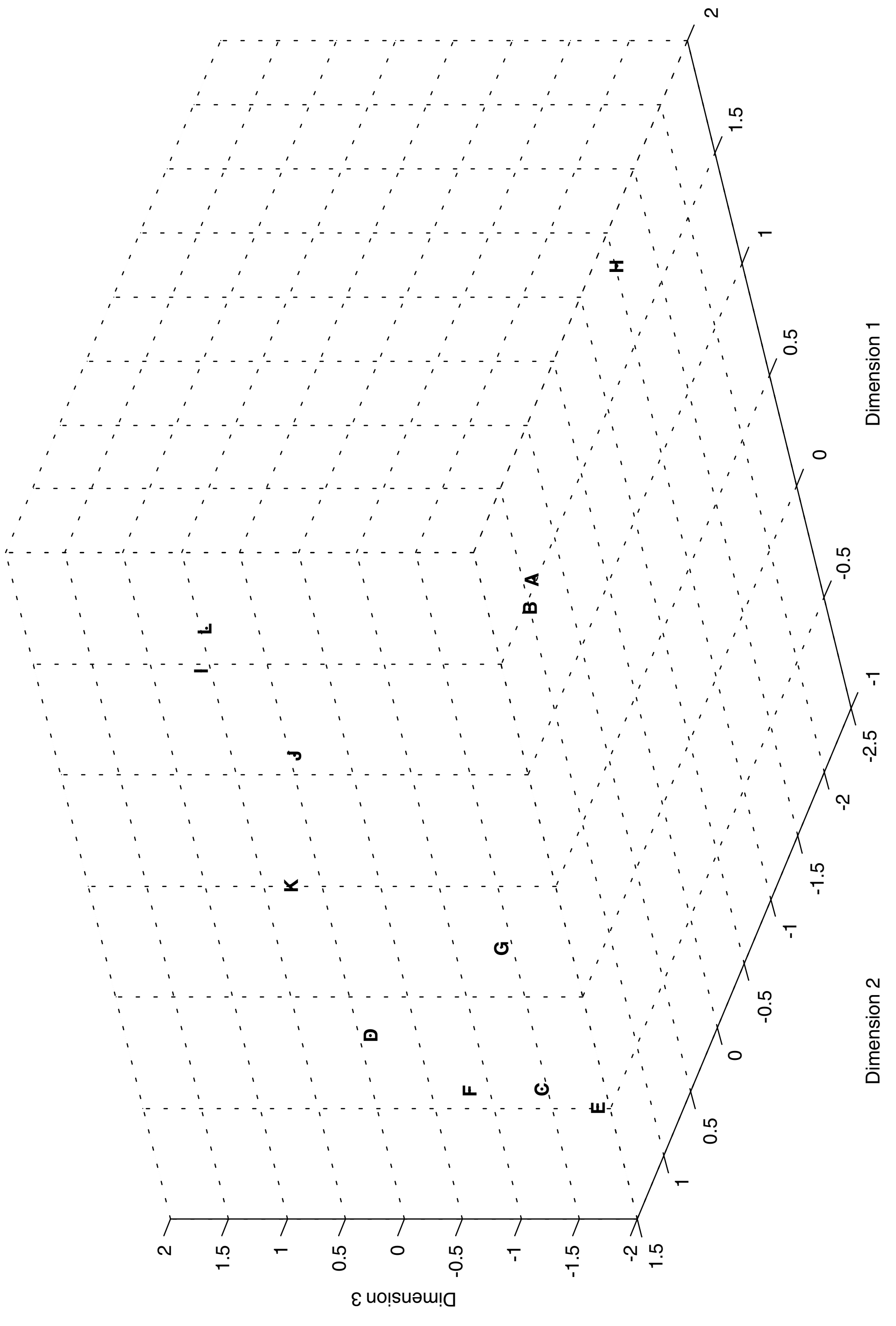

Figure 6. Aggregate market map from ALSCAL for portable phones

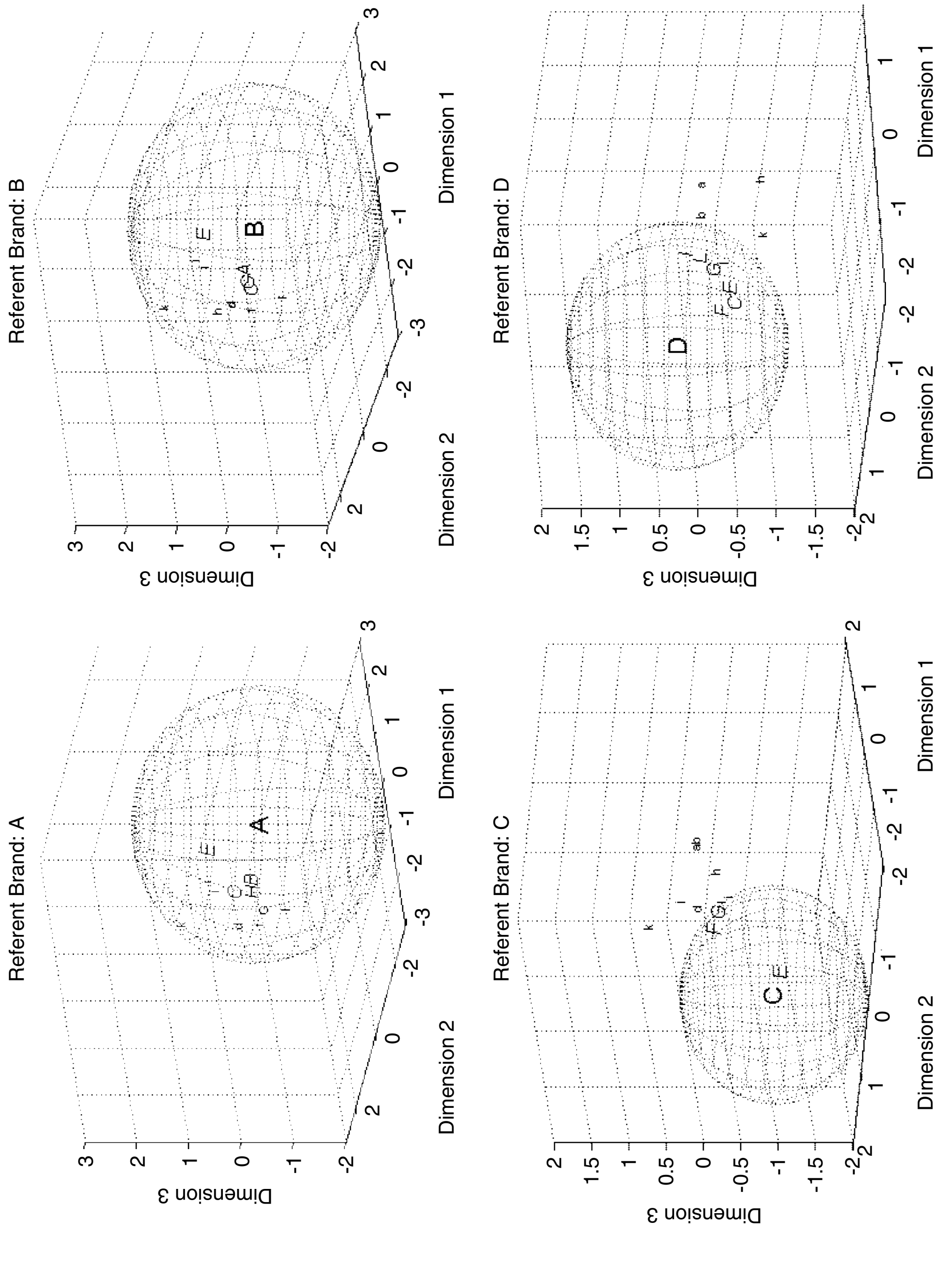

Figure 7a. Brand-specific maps for portable phones

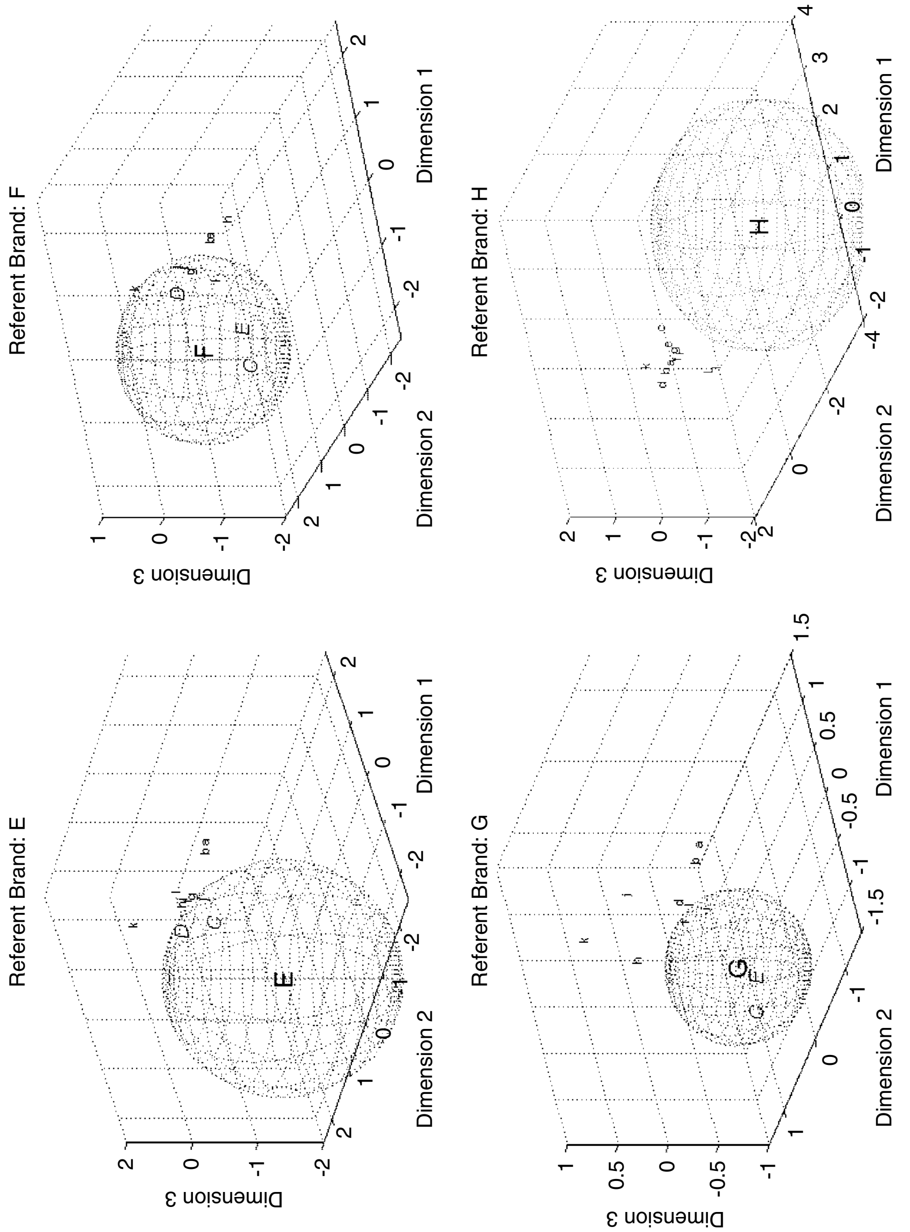

Figure 7b. (*Continued*)

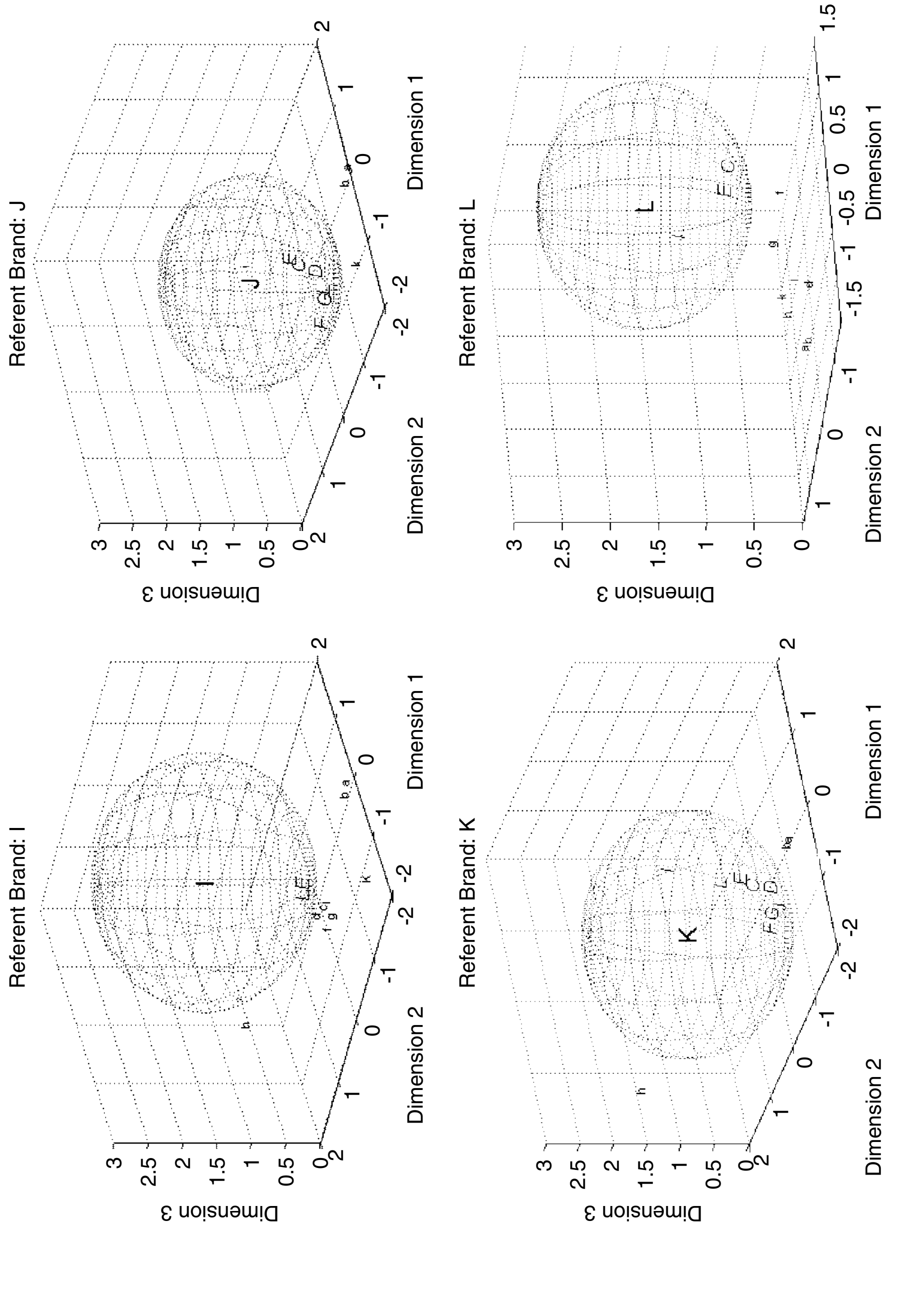

Figure 7c. (*Continued*)

with their own different radii as estimated by our procedure. For referent brand A, our proposed model estimates brands B, C, and E to be located within its competitive sphere; for brand B, it is brands A, C, E, and G; for brand C, it is brands E, F, and G; for brand D, it is brands C, E, F, G, I, and L; for brand E, it is brands C, D, and I; for brand F, it is brands C, D, and E; for brand G, it is brands C and E; for brand H (lowest price, fewest features), no other brand falls in its competitive sphere; for brand I, it is brands E and L; for brand J, it is brands C, D, E, F, G, and L; for brand K, it is brands C, D, E, F, G, J, and L; and for brand L, it is brands C, E, and I.

Again, as in the luxury automobile application, the derived aggregate ALSCAL map in Figure 6 masks much of this brand-specific asymmetric competition. As shown in Figure 7, different asymmetric scenarios are obtained by the application of our proposed MDS methodology that do not exactly follow the implications of the aggregate MDS derived map.

DISCUSSION

Scholars of market structures, from both the supply and demand perspectives, increasingly recognize that competitive market structures are asymmetric (e.g., Carpenter *et al.*, 1988; Chen, 1996). Nonetheless, empirical research to assess competitive asymmetry has been lacking (e.g., Chen, 1996), which creates an urgent need to devise methods to uncover these competitive asymmetries. We have integrated literature on the supply and demand perspectives to suggest that they are more complements than substitutes, though for discerning competitive asymmetries the demand perspective may have a slight edge. To advance thought on empirically uncovering asymmetric competitive market structures, we have proposed a new stochastic MDS methodology that employs consumer demand information (choice sets) to identify and represent asymmetric competitive market structures. Because discerning competitive asymmetry is critical (e.g., Chen, 1996), we present an easily executable methodology in an MLE framework that allows for hypothesis testing. We also demonstrate the means to represent these competitive asymmetries spatially, which should aid in managerial information processing of the competitive market structure faced by any firm or brand. Furthermore, we provide various theoretical bases for the emergence of competitive asymmetries. From the standpoint of a strategist, understanding such competitive asymmetries is critical for evaluating current strategic programs and gauging future competitive threats and opportunities.

Implications

As we showed with the luxury car and portable telephone choice set applications, competitive insights can be obtained from the use of the proposed spatial MDS methodology that are much richer and more detailed than results obtained from more traditional approaches. Because we are unable to disclose the particular brand names studied in the portable phone application, we use the luxury car application as an illustration for the insights that can be garnered from this research. The symmetric competitive market structure depicted in Figure 2, obtained from an aggregate ALSCAL analysis, implies that competition for all brands is structured along two dimensions: domestic vs. foreign and GM vs. Ford. In particular, consumer considerations appear to group into three brand subgroups: two domestic Ford brands (Continental and Town Car), three domestic GM brands (Seville, Riviera, and Olds98), and five imports (Mercedes 300E, BMW325i, Volvo 740, Jaguar XJ6, and Legend). As indicated by Figure 2, consideration/competition appeared to be limited to those brands within the three groups separately. That is, according to traditional symmetric approaches, consumers will consider only one of these three subgroups and then jointly consider the luxury vehicles in that subgroup as potential replacements.

However, the proposed methodology reveals that this 'grouping' phenomenon is an overly restrictive and simplistic way of depicting the competitive market structure for this set of 10 brands and completely ignores competitive asymmetry. Some general findings are quite interesting here. On the domestic side, the model predicts that foreign cars will not be jointly considered with any of the domestic brands. However, within the set of domestic vehicles, we witness quite different competitive sets defined by the threshold regions that display significant competitive asymmetries. For example, the Lincoln Town Car is contained within the consideration set of all its domestic and foreign counterparts, yet no domestic or foreign brand is within its threshold consideration region—an example of very strong positioning!

A very different portrayal of a competitive market structure occurs with the foreign imports. We see a larger threat from the domestic brands (primarily from the Town Car) than vice versa. The estimated referent brand maps in Figures 3–5 provide a much more detailed portrait of the competitive market structure faced by each brand than that derived by Figure 2 with traditional MDS. In addition, confirmatory evidence rejects the common space restriction (symmetry) through the maximum likelihood estimation (MLE)-based information heuristics compared with the full asymmetric model. It is critical to note that from a resource allocation perspective, the asymmetric maps provide a very different perspective than the symmetric map. The symmetric map suggests that a foreign firm should focus its resources on other foreign firms, whereas the asymmetric maps reveal considerable competition between domestic and foreign firms.

So what does the asymmetric approach proposed here give strategists above and beyond the traditional symmetric map obtained from SPSS? At least six advantages of the asymmetric approach we propose are pertinent for strategic management and marketing.

1. *The symmetric traditional MDS solution does not provide an accurate picture of competition in the two markets studied*. For example, Figure 2 implies that the Riviera is the prime competitor of the Olds98 (and vice versa), both GM products. This result suggests that GM should be more worried about possible product cannibalization than any competitive threat. However, the referent brand map of the Olds98 (Figure 4) shows that its prime competitive threat comes from the Town Car, a Ford product. Furthermore, given that the Olds98 is not a prime competitive threat to the Town Car (Figure 3), Oldsmobile managers should focus on repositioning to strengthen their weak competitive position rather than any cannibalization issues. Along similar lines, the aggregate symmetric map for portable telephones (Figure 6) shows that brands B and C do not compete with each other, whereas the brand-specific asymmetric competitive maps show that brand C seems to compete with brand B but brand B does not compete with brand C (Figure 7).
2. *The assumption that competition is symmetric is naïve and can potentially lead to myopic strategic thinking*. For example, the symmetric map (Figure 2) shows that competition occurs among the three GM brands (Olds98, Rivera, and Seville), whereas the asymmetric maps in Figure 4 show that the Town Car is their primary competitive threat. Moreover, the map for the Town Car shows that none of the GM brands is a competitive threat for it. The asymmetric maps thus give managers the opportunity to identify situations of competitive weakness, in which a brand (Town Car) competes with their brands (Olds98, Rivera, and Seville) but their brands do not compete with it. In such a situation, the managers of GM should work toward reducing the competitive threat from the Town Car and/or increasing their competitive threat to it. That is, strategy can be examined in terms of its offensive and defensive components. Brands with weak and strong competitive positions are also visible in the brand-specific maps of the portable phone example (Figure 7). Brand E seems to have a strong competitive position, as no other brand is close to it, but it is also fairly close to many other brands, as shown by the brand maps of brands A, B, C, D, and F.
3. *Asymmetric maps can be used to introduce and position new products*. For example, a new entrant that is aware of the competitively superior positioning of the Town Car could adopt a me-too strategy and position itself close to the Town Car by employing a comparative advertising strategy. Thus, by being similar to Town Car, the new entrant may be more likely to be perceived as having the same strengths. Alternatively, the market entrant could position itself as highly differentiated from the Town Car so that it does not compete with the Town Car and nor does the Town Car compete with it. The information gleaned from these asymmetric maps can be even more useful when combined with information from other sources, such as market share, that provide information on the demand for competing brands.
4. *Managers can use information on competitive asymmetry to reposition existing brands*. For example, BMW 325i faces stiff competition from Acura Legend, Mercedes 300E, Volvo

740, and the Town Car, though it is not a primary competitive threat to any of these or the other brands we studied. Clearly, the positioning of BMW 325i is weak; it should either strengthen this position or reposition. Managers of the BMW 325i need to be aware that they largely compete with imports and might communicate with consumers to strengthen this position to enter the referent maps of other imports. Alternatively, given the positional strength of the Town Car, BMW 325i managers might consider a me-too strategy to reposition closer to it.

5. *The brand-specific maps can be used to manage brand portfolios*. For example, the brand maps for the GM brands (Figure 4) show that the Town Car is the primary competitor for three brands (Seville, Rivera, and Olds98), that they experience some cannibalization threats, and that the three GM brands are not in the competitive set for the Town Car. These three findings seem to suggest that the three GM brands are positioned close to one another and have much weaker positions than the Town Car's. GM would be advised to create greater heterogeneity among the brands in its portfolio and position them more strongly against the Town Car.
6. *At the firm level, the maps can be useful in resource allocation decisions*. Managers can use the maps to allocate resources to better manage their brand portfolios. For example, GM should recognize the unique positioning of the Town Car, which seems to provide it competitive invisibility. In contrast, the maps also reveal the competitive weakness of the other GM brands like the Olds 98. Thus, GM may be better off expending resources on maintaining and strengthening its Cadillac and Buick brands and consider withdrawing Olds98 from the market. Perhaps such reasoning provided the basis for GM's recent elimination of its Oldsmobile division completely.

Finally, the results can be used to draw additional implications at the firm or strategic business unit level, which goes beyond brand portfolio management. To achieve this objective, managers would have to create aggregate indices based on a specific indicator, such as market share or profitability. For example, consider the competition between GM and Ford. For simplicity, assume that the three GM brands have approximately the same market share (each has a weight of 33.3%), as do the four Ford brands (each has a weight of 25%). Because Ford has at least one brand that competes with the three GM brands (Town Car), the GM–Ford index equals 1. However, because GM has no brand that competes with the four Ford brands, the Ford–GM index equals 0. Thus, the competitive asymmetry favors Ford and puts GM in a disadvantageous position. Similarly, we could construct cannibalization indices. For GM, Olds98 competes with Riviera, thus making the cannibalization index for GM $= 0.33$. For Ford, the Town Car competes with the other three brands, making the cannibalization index for Ford $= 0.75$. Thus, cannibalization seems to be a greater problem for Ford than GM. Although these insights from aggregation are valuable, the old maxim that aggregation can lead to biases is applicable here. One should be cautious when aggregating and use multiple criteria (e.g., market share, growth rate, profitability) to ensure the conclusions are robust.

Directions for future research

Given the promising results obtained in the luxury car and portable telephone market applications, some areas for further research arise. In applications in which both binary consideration set judgments and preference/intention to buy ratings are collected, researchers could use both sets of data to construct maps (see DeSarbo and Jedidi, 1995). Also, a latent structure analog to this proposed MDS-based methodology would be very enlightening, because we might expect potential market segment differences in competitive market structure and respective asymmetry. This methodological extension would accommodate situations with different underlying *unknown* market segments that have different choice sets. However, it would necessarily entail the estimation of many more parameters as the conditional brand coordinates would have to be estimated by derived market segment (i.e., one would need to estimate S times more parameters than the proposed MDS model, where S is the number of derived market segments).

Furthermore, researchers should identify other demand- and supply-based approaches to extend this approach. For example, generalizing the proposed methodology to other types of survey data, such as continuous preference or dominance judgments (e.g., intention to buy scores), would prove valuable for applicability. Similarly, devising supply-based methodologies to discern competitive asymmetry would prove useful. The proposed spatial methodology can be employed with supply-side binary data (e.g., managers from different manufacturers identify whom they perceive as their major competitors). Consistent with the recommendations of Day (1981), devising appropriate methodology that uses both demand- and supply-based data may prove even more beneficial.

Finally, from a theoretical standpoint, it is important to study how and why competitive asymmetries and asymmetric market structures develop.[2] Perhaps the most promising avenue for exploring this issue lies in the heuristics and biases in human decision-making (e.g., Kahneman *et al.*, 1982). Human decision making in the development of market structures appears in various areas (e.g., including managerial, consumer, stakeholder). In each of these areas, human decision-making involves heuristics and biases that might lead to competitive asymmetries.

CONCLUSION

At the very heart of strategic management lies the question: Who competes with whom? Unfortunately, there are no simple answers to this critical question. Although there seems to be recognition in the literature that competitive structures are asymmetric, methodologies to identify and represent such asymmetries have been lacking. We take important steps in integrating demand- and supply-based perspectives and devising a new stochastic MDS technique that can identify and spatially represent asymmetric competitive market structures in any industry that provides demand- or supply-based data. Our integration of the demand- and supply-based perspectives suggests that a complete picture of competitive market structures is more likely to emerge when the two perspectives are considered together. The demand-based perspective can calibrate the supply perspectives and vice versa; in the best-case scenario, they can be used in tandem to uncover critical insights. From a methodological standpoint, we develop statistical tests to compare symmetric vs. asymmetric competitive market structures and demonstrate in two different product classes that the asymmetric portrayals of competitive market structure clearly dominate. Our research demonstrates the inherent asymmetric nature of competitive market structures and highlights the vitality of this research. The implications of this research for practice are evident from our findings in both the U.S. luxury automobile and portable telephone communication industries.

[2] We thank an anonymous reviewer for encouraging us to think along these lines.

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