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Millions of marketing dollars are spent each year around the world, publicly and privately, to develop and support brand names. Nothing is more important to brand managers than the ability to measure and understand consumer brand associations, the responses that are evoked when consumers think about brands.

Building on previous work (Henderson, Iacobucci, and Calder 1998), in this paper the same authors present methods for studying consumer brand associations. They compare two techniques for measuring consumers' perceptions of products and consumers' loyalty to brand names: multidimensional scaling and associative networks.

Multidimensional scaling (MDS), a popular traditional technique for marketing researchers, graphically maps how people view and differentiate brands. Similar brands are represented as points close in space, and dissimilar brands are placed further apart. Associative networks represent consumer knowledge as links of associations among "nodes," or units of information such as brands, attributes, advertisements, etc. While marketers agree that network models are well suited to studying consumer judgment, apparently no marketing research has yet used associative networks to detect branding effects and strategies.

In a branding experiment, the researchers use both techniques to examine primary brand concepts: positioning, complementarity, and substitutability. Subjects were asked to evaluate sports cars before and after being exposed to hypothetical new car introductions.

Results showed both MDS and associative network methods to be useful for examining brand positioning (in particular, to diagnose brand dilution or to identify potential features to brand). MDS, however, was not able to distinguish between complementarity and substitutability, that is, between brands that were associated in consumers' minds (and therefore candidates for complementary brand action such as co-branding), and brands that were similar (and therefore substitutable competitors in the minds of the consumers). Associative networks were able to distinguish these two very different branding effects.

Overall, however, the research shows that traditional mapping of perceptions and associative networks can work together to define the relationship of one brand to another. The brand researcher wishing to be well informed would use both techniques.

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Introduction

Brand equity, brand image, and brand knowledge are built upon brand associations and consumer perceptions (e.g., Keller 1993; Farquhar and Herr 1993; Schmitt, Tavassoli, and Millard 1993). Consumer brand associations are those perceptions, preferences, and choices in memory linked to a brand (Aaker 1991). These associations can vary from physical product attributes to the activity evoked in conjunction with the brand. For example, "Pepsi" may evoke attributes such as sweetness or competing brands (e.g., Coca-Cola), as well as associations to people (e.g., Michael Jackson), places (e.g., a rock concert), and usage (e.g., thirst, a birthday party).

Brand associations create value for the focal product in several ways (Aaker 1991). Associations help consumers process information, hopefully providing purchase motivation (e.g., Tybout, Calder, and Sternthal 1981). Brand associations can also provide a basis for new products and brand extensions; for example, Marriott's "no frills" Courtyard brand (Ulrich and Lake 1991).

In the literature to date, marketing researchers present a wide array of branding effects, including co-branding (Spethmann and Benezra 1994), cannibalization (Arnold 1992), brand parity and brand confusion (Aaker 1991; Kapferer 1995), and brand dilution (Loken and John 1993; Broniarczyk and Alba 1994). Since marketers are also interested in the associations that consumers hold for brands, it is important to determine how these associations are arranged in consumers' minds. This paper presents methods for studying consumer brand associations.

We are interested in empirical representations of consumer perceptions of brand properties and market structure, not *a priori* managerial statements of intended brand strategies; thus, we explore models for understanding data that represent consumer associations. A classic means of analyzing consumer perceptions is multidimensional scaling (MDS). Against this standard benchmark, we compare the analytical associative network methods for representing consumer perceptions. Developed primarily in cognitive psychology, the associative network approach is based on a stronger theoretical tradition than MDS. Yet to date, it is not leveraged sufficiently in marketing or consumer behavior (Krishnan 1996); no marketing research has yet used associative networks to detect branding effects and strategies.

For this investigation, the paper is organized as follows. The first section contains a brief review of the type of data and results that a researcher would obtain via MDS. In the second section, we present the conceptual background on associative networks and network methods, followed by a section in which we consider several classes of branding effects.

In the final section, we pursue these conjectures with an empirical test: Consumers are exposed to information about a purported, forthcoming brand extension. Some consumers make proximities judgments (i.e., judgments of similarities among brands), and their perceptions are represented as MDS plots. Others make judgments of associative links, and their perceptions are represented as associative networks. For both groups, the post-manipulation perceptions are compared to those held prior to the intervention, and we examine each technique for its sensitivity to perceptual change in brand cognitions.

Multidimensional Scaling

MDS has been a popular traditional technique for marketing researchers interested in consumers' views of brands and products (Arabie, Carroll, and DeSarbo 1987; Carroll and Arabie 1998; Kruskal and Wish 1991; Malholtra 1994; Shocker and Srinivasan 1979). The mapping technique is based on spatial distance representations: pairwise similarities judgments are modeled so that similar brands are represented as points close in space, and brands that are different are placed further apart (Green, Carmone, and Smith 1989; Davidson 1983).[1]

Three types of data are usually collected in an MDS study. First, perceptions of proximities (i.e., similarities) among the brands form the basis for determining the perceptual map. Second, ratings of the brands along a number of attributes allow for vectors to be added to the map to enhance its interpretability. Third, consumer preference judgments are added in the form of ideal points, which are useful in locating consumer segments and in opportunity analysis. MDS methods involving these three kinds of data are so well understood that, presumably, any branding effect requiring an understanding of similarities, attributes, or preferences would be served well by the MDS model.

Note, however, that there is little cognitive theorizing to support the idea of mental maps based on the assumption that consumers hold spatial representations in their minds. Nevertheless, MDS has been extremely useful as an analogue, much as factor analysis is a useful analytical method, even if we do not believe that consumers implicitly compute correlations among indicator variables. Furthermore, MDS has not been explored as a means of understanding branding effects. In this novel use of the technique, we will examine its ability to identify certain aspects of changes in brand perceptions.

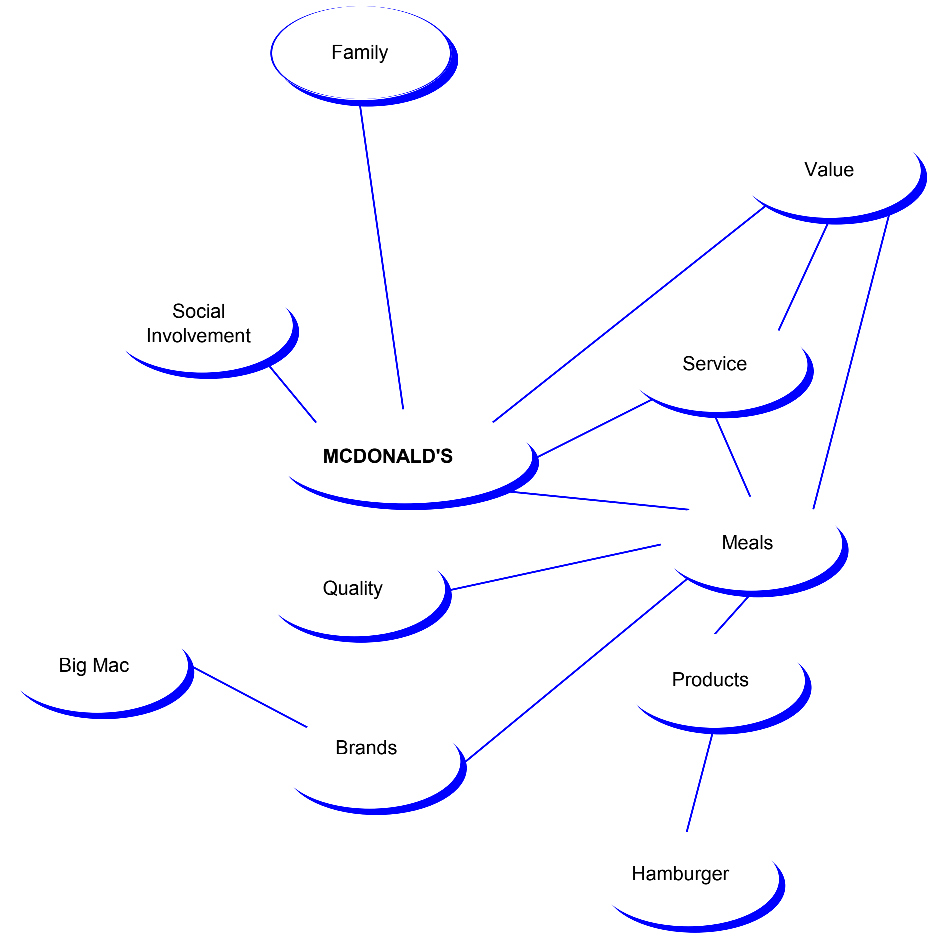
Associative Networks and Network Methods

Although MDS is the technique of choice for perceptual mapping in marketing, associative networks may provide a more valid representation of consumers' cognitive processes.

It is commonly held that consumers store information in memory in the form of associative networks (also known as mental models, or knowledge structures). Cognitive psychologists have been studying such networks for some time (e.g., Anderson and Bower 1973; Collins and Loftus 1975; Ellis and Hunt 1992; Gentner and Stevens 1983). In general, these researchers contend that knowledge is represented as links of associations among concept nodes (cf. Sirsi, Ward, and Reingen 1996; Ward and Reingen 1990). The nodes are units of information such as brands, attributes, advertisements, etc., and the links contain the relational tie between the concepts (e.g., a brand "possesses" much of an attribute, and a brand image is "like" the spokesperson).

Consider the cognitive structure depicted in Figure 1 (from Aaker 1996). The nodes in this associative network include a firm name (i.e., McDonald's), a product brand name (Big Mac), a generic product category (hamburger), features of the products (e.g., quality, service), and people and activity (family, social involvement). The links make various associations by connecting nodes together to form a network of ideas, or a knowledge structure.[2]

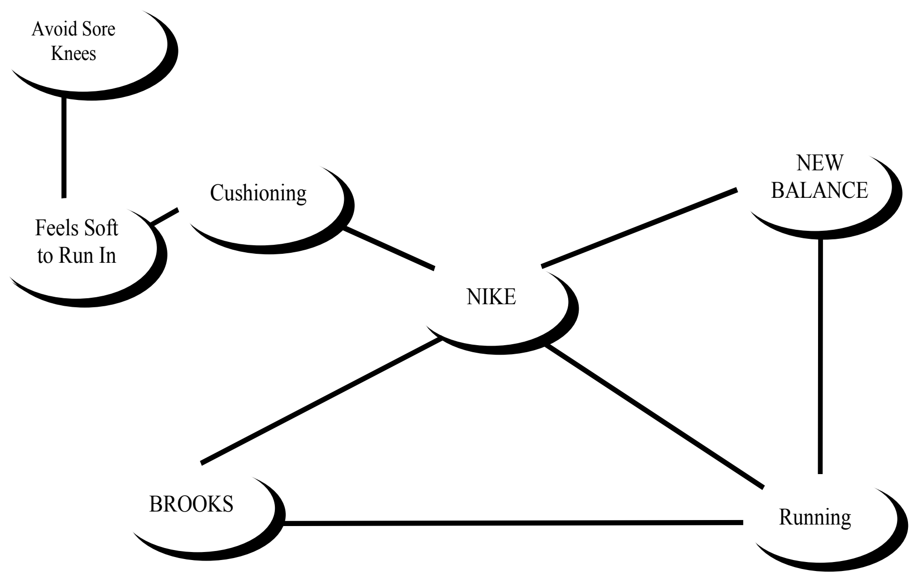
Figure 1. Aaker (1996) Associative Network



Collins and Loftus (1975) developed an influential network model using the concept of spreading activation: When a person is reminded of a stimulus (e.g., an ad for McDonald's), activation of that node occurs and spreads first to the nodes that are directly connected, and eventually to the other nodes that are indirectly connected. Spread is thus a function of the distance from the stimulus node, and memory retrieval of one item produces the fastest activation to those other items that are closely related and most directly linked.

McDonald's is the focal firm in Figure 1, and the map is useful to the brand manager who wishes to better understand McDonald's brand perceptions. No competitive brands or firms exist in that particular example network, however, so it yields no information about market structure. In contrast, consider the network in Figure 2, presented by Peter and Olson (1993), which contains three brands of running shoes (Brooks, Nike, and New Balance). Note that Brooks and New Balance are connected only indirectly to each other through Nike, which leads us to hypothesize that consumers making purchase decisions are less likely to perceive these two brands as similar or as competitors. Only Nike is also associated with the property of "cushioning," a presumably desirable attribute, and one that is only indirectly linked to the other brands.

Figure 2. Peter and Olson (1993) Network



Marketers agree that such network models are well-suited theoretically to studying consumer memory (Bettman 1971, 1974; Calder and Gruder 1989; Schmitt et al. 1993; Sirsi et al. 1996). Although many cognitive theories of consumer behavior posit associative network structures (e.g., Hutchinson 1989; Keller 1998), rarely are they elicited or modeled empirically. By representing brand associations as networks, structural data can be modeled in a manner most consistent with the prevalent theoretical views of consumer memory structure. In the sections that follow, we first discuss how to collect brand associations data, and then describe models for the network linkages.

Eliciting Associative Network Data

Consumer brand associations can be elicited by a variety of data collection methods, including free association and response (Boivin 1986; Green, Wind, and Jain 1973; Krishnan 1996; Steenkamp, Van Trijp, and Berge 1994; Olson and Muderrisoglu 1977), laddering (Reynolds and Gutman 1988), and pairwise similarity judgments (Hauser and Koppelman 1979). The latter proximities ratings are those most closely associated with MDS; the researcher provides the list of brands in the perceptual consideration set as well as the attributes he or she deems relevant.

For comparison, we will use a more qualitative method called the repertory grid. It is based on a freer, less structured associative task, which is presumably more consistent with the goal of uncovering associations. Respondents choose their own stimulus brands and the attributes that they personally believe to be relevant for the comparisons (Kelly 1955; Sampson 1972; Steenkamp and Van Trijp 1997; Zaltman 1997; Zaltman and Coulter 1995).

Participants begin by naming some number (e.g., seven) of the products of interest (e.g., sports car brands). Groups of three brands are compared at a time, using a procedure called triadic elicitation (Shaw 1981). Specifically, respondents are asked in what way two brands are alike and how the third differs. These judgments allow comparisons between brands, using associations of any kind. For example, a respondent who evaluated Porsche, Jaguar, and Camaro said that the first two were "European" whereas Camaro "lacked mystique." Note that these associations do not necessarily constitute simple bipolar judgments. The attributes that distinguish the brands are collected over multiple triads for each respondent.

The data for each respondent, or an aggregate view over many respondents, can be viewed either in table format or diagrammatically. We choose the latter form so that the data represented are similar to the networks in figures 1 and 2. Essentially, consumer-perceived associations between brands and attributes will be represented as links, as will similarities between brands or between attributes. The procedure for obtaining network figures is detailed below. We provide a step-by-step description of the matrix computations for one respondent, and then discuss aggregation over multiple respondents.

A respondent's data describing judgments of m brands on n attributes were tabulated into the n x m matrix, **X**, presented in Table 1. This subject yielded the seven brands of sports cars: Porsche, Lamborghini, Nissan 300ZX, Jaguar, Benz, Camaro, and Corvette. The triadic distinctions resulted in a total of five attributes: lack of mystique, shape, classy, low price, and non-European. Brands associated with the attribute are marked with 1. A zero indicates that the brand is not associated with the attribute. For example, Nissan, Camaro, and Corvette are associated with the properties "no mystique" and "low price." Porsches are seen as common in shape and classy, etc.[3]

Table 1. Elicited Associative Matrix, X

	Porsche	Lamborghini	Nissan 300ZX	Jaguar	Benz	Camaro	Corvette
No Mystique	0	0	1	0	0	1	1
Common Shape	1	1	0	1	0	0	0
Classy	1	1	0	1	1	0	0
Low Price	0	0	1	0	0	1	1
Non-European	0	0	0	0	0	1	0

In order to study the associations among the brands (vis à vis the attributes) and those among the attributes (with respect to the brands), we compute the sums of squares and cross-products matrices, **X'X** and **XX'** respectively, which appear in tables 2 and 3. The off-diagonals of **X'X** represent the number of attributes shared by brands *i* and *j,* and the diagonal entries represent the total number of attributes associated with brand *i*. For example, Porsche, Lamborghini, and Jaguar share two attributes, whereas they have nothing in common with Nissan, Camaro, or Corvette. This matrix gives the brand manager a sense of consumer-perceived market structure.

Table 2. Brand Matrix, X'X

	Porsche	Lamborghini	Nissan 300ZX	Jaguar	Benz	Camaro	Corvette
Porsche	2	2	0	2	1	0	0
Lamborghini	2	2	0	2	1	0	0
Nissan 300ZX	0	0	2	0	0	2	2
Jaguar	2	2	0	2	1	0	0
Benz	1	1	0	1	1	0	0
Camaro	0	0	2	0	0	2	2
Corvette	0	0	2	0	0	2	2

Table 3. Attributes Matrix, XX'

	No Mystique	Shape	Classy	Low Price	Non-European
No Mystique	3	0	0	3	1
Shape	0	3	3	0	0
Classy	0	3	4	0	0
Low Price	3	0	0	3	1
Non-European	1	0	0	1	1

Analogously, **XX'** yields the associations among the attributes, with the off-diagonals representing the number of brands that have both attributes *i* and *j,* etc. Note for example that no brands were perceived as both being classy and yet having no mystique. This matrix gives the brand manager a picture of what qualities coexist in the products in the marketplace.

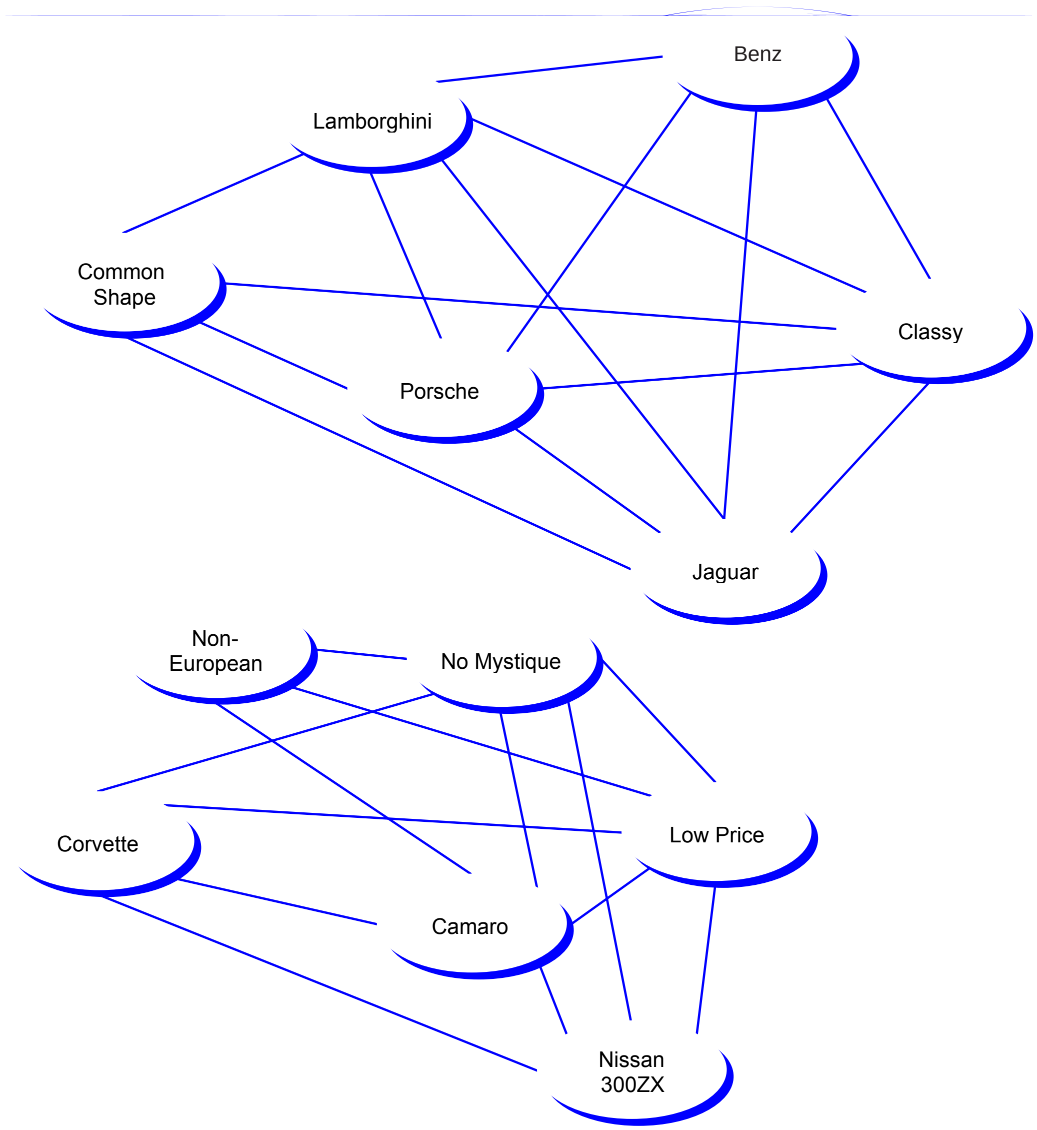
The matrix in Table 4 is the full associative matrix. It contains **X** as the lower-left submatrix, **X'** in the upper right. The binary version of **X'X** appears in the upper-left of the associative matrix (all entries that had been ≥ 1 have been set equal to 1), and the binary version of **XX'** appears in the lower-right of the supermatrix.[4]

Table 4. Associative Matrix, A

	Brands							Attributes				
	Pors	**Lamb**	**ZX**	**Jag**	**Benz**	**Cam**	**Vett**	**Nomy**	**Sh**	**Clas**	**LoPr**	**NoEu**
Porsche	1	1	0	1	1	0	0	0	1	1	0	0
Lamborghini	1	1	0	1	1	0	0	0	1	1	0	0
Nissan 300ZX	0	0	1	0	0	1	1	1	0	0	1	0
Jaguar	1	1	0	1	1	0	0	0	1	1	0	0
Benz	1	1	0	1	1	0	0	0	0	1	0	0
Camaro	0	0	1	0	0	1	1	1	0	0	1	1
Corvette	0	0	1	0	0	1	1	1	0	0	1	0
No Mystique (Nomy)	0	0	1	0	0	1	1	1	0	0	1	1
Shape (Sh)	1	1	0	1	0	0	0	0	1	1	0	0
Classy (Clas)	1	1	0	1	1	0	0	0	1	1	0	0
Low Price (LoPr)	0	0	1	0	0	1	1	1	0	0	1	1
Non-European (NoEu)	0	0	0	0	0	1	0	1	0	0	1	1

This matrix contains all the information we need to proceed further; however, sometimes it is easier to detect patterns when data are depicted diagramatically.[5] For example, in the matrix, it is difficult to discern that the brands and attributes actually split into two distinct groups, with some brands being described by some attributes but not others, etc. Thus, the data in the table are presented as a network graph in Figure 3. Every matrix element in Table 4 that is a "1" is represented by a link between the nodes in the figure.[6] The specific placement of the nodes is not important in graphing networks, but the graph must faithfully depict the connections. In this figure, we see that a picture is worth a megabyte of words. Consumers perceive the European brands as classy, but having a common shape, and the American brands as not mysterious, low priced, and, of course, non-European.

Figure 3. Associative Network Corresponding to Table 4



It is also important to consider how the judgments of multiple respondents are gathered into a single aggregate view. We shall see that network aggregation is no different from any other kind of average, in that it cannot perfectly represent each individual datum component of the aggregate. To be analogous to our efforts in the rest of this paper, we will compare the aggregation of data in an MDS representation to associative networks.

Generally, to aggregate data in an MDS representation, pairwise similarities data are simply averaged, and then the single matrix of mean similarities is input to an MDS algorithm. Alternatively, the individual matrices can be input to an individual differences algorithm, which then creates its own average group space. Computing these means, or allowing the computer to do so, is quite straightforward.

With data captured in the more qualitative technique of repertory grids, the aggregation process is not as simple. Consider again Table 4, the associative network for an individual consumer. We had such data available for nine subjects, and we developed a superset grid that contained all brands and attributes elicited across all subjects. If a subject provided an evaluation of a particular car on a particular attribute, that evaluation was entered into the corresponding cell of the matrix. However, if a given subject did not provide such an evaluation, because either the car or the attribute was not one that they had generated, then the cell was filled with a 0.

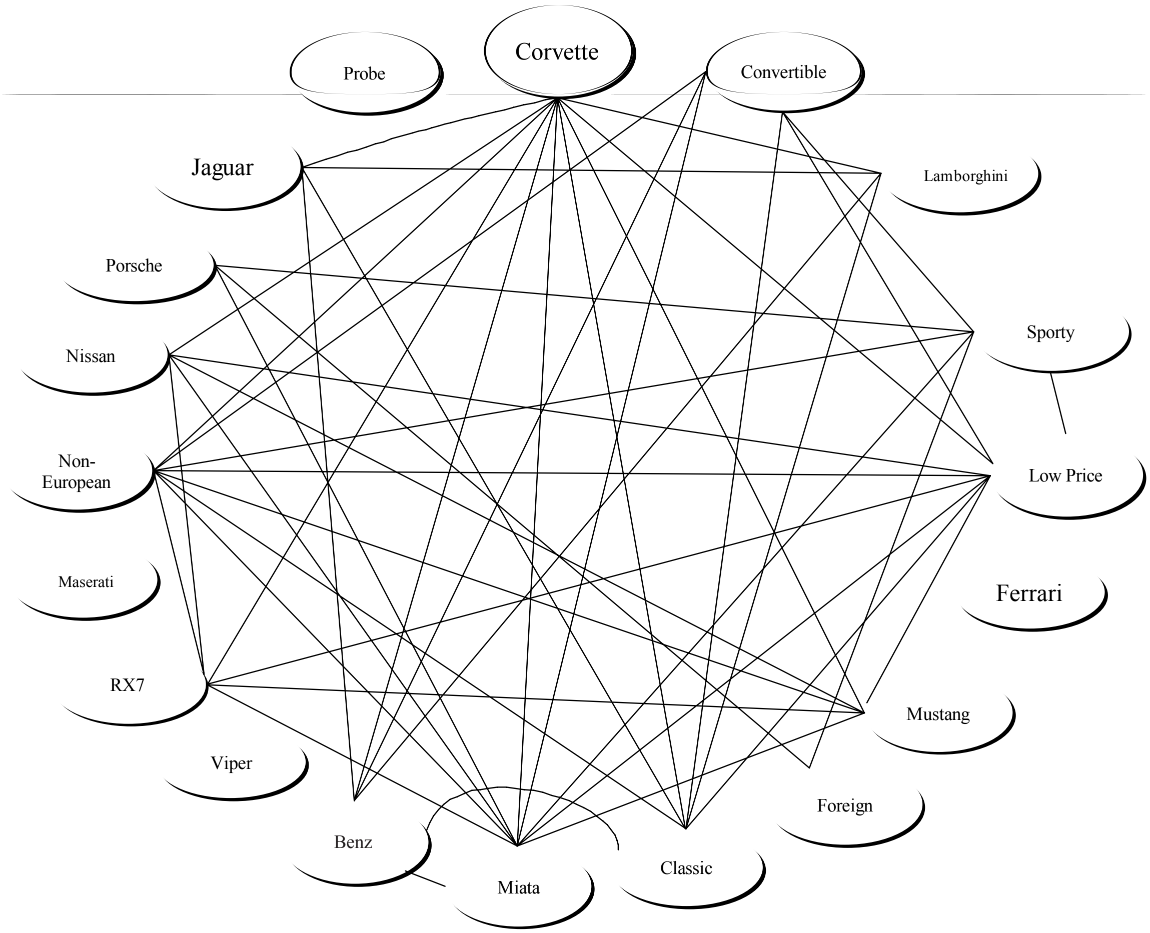
Each person's super-grid was then dichotomized (for simplicity), and these matrices were summed across all individuals. To begin to minimize totally idiosyncratic responses, those cells containing at least a 2 (i.e., indicating agreement among at least two consumers) were set equal to 1 and were represented in the resulting network figure as ties. Those cells for which only one person made a judgment were set to 0 (again, the strengths of valued ties could be retained or the threshold changed; the dichotomization is for simplicity of presentation). The resulting aggregate full associative matrix A is shown in Table 5, and the corresponding network appears in Figure 4.

Table 5. Aggregate Full Associative Matrix, A

	BRANDS													DIMENSIONS					
	VETT	FERR	JAG	LAMB	MASR	BENZ	MIAT	MUST	NISS	PORS	PROB	RX7	VIPE	TRAD	CONV	FRGN	LOPR	NOEU	SPTY
Corvette	1	0	1	1	0	1	1	1	1	0	0	1	0	1	0	0	1	1	0
Ferrari	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Jaguar	1	0	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Lamborghini	1	0	1	1	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0
Maserati	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Benz	1	0	1	1	0	1	1	0	0	0	0	0	0	1	1	0	0	0	0
Miata	1	0	0	0	0	1	1	1	1	1	0	1	0	0	1	0	1	1	1
Mustang	1	0	0	0	0	0	1	1	1	0	0	1	0	0	0	0	1	1	0
Nissan	1	0	0	0	0	0	1	1	1	0	0	1	0	0	0	0	1	1	0
Porsche	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0	0	1
Probe	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RX7	1	0	0	0	0	0	1	1	1	0	0	1	0	0	0	0	1	1	0
Viper	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Traditional	1	0	1	1	0	1	0	0	0	0	0	0	0	1	1	0	1	1	0
Convertible	0	0	0	0	0	1	1	0	0	0	0	0	0	1	1	0	1	1	1
Foreign	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1
Low Price	1	0	0	0	0	0	1	1	1	0	0	1	0	1	1	0	1	1	1
Non-European	1	0	0	0	0	0	1	1	1	0	0	1	0	1	1	0	1	1	1
Sporty	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	1	1	1	1

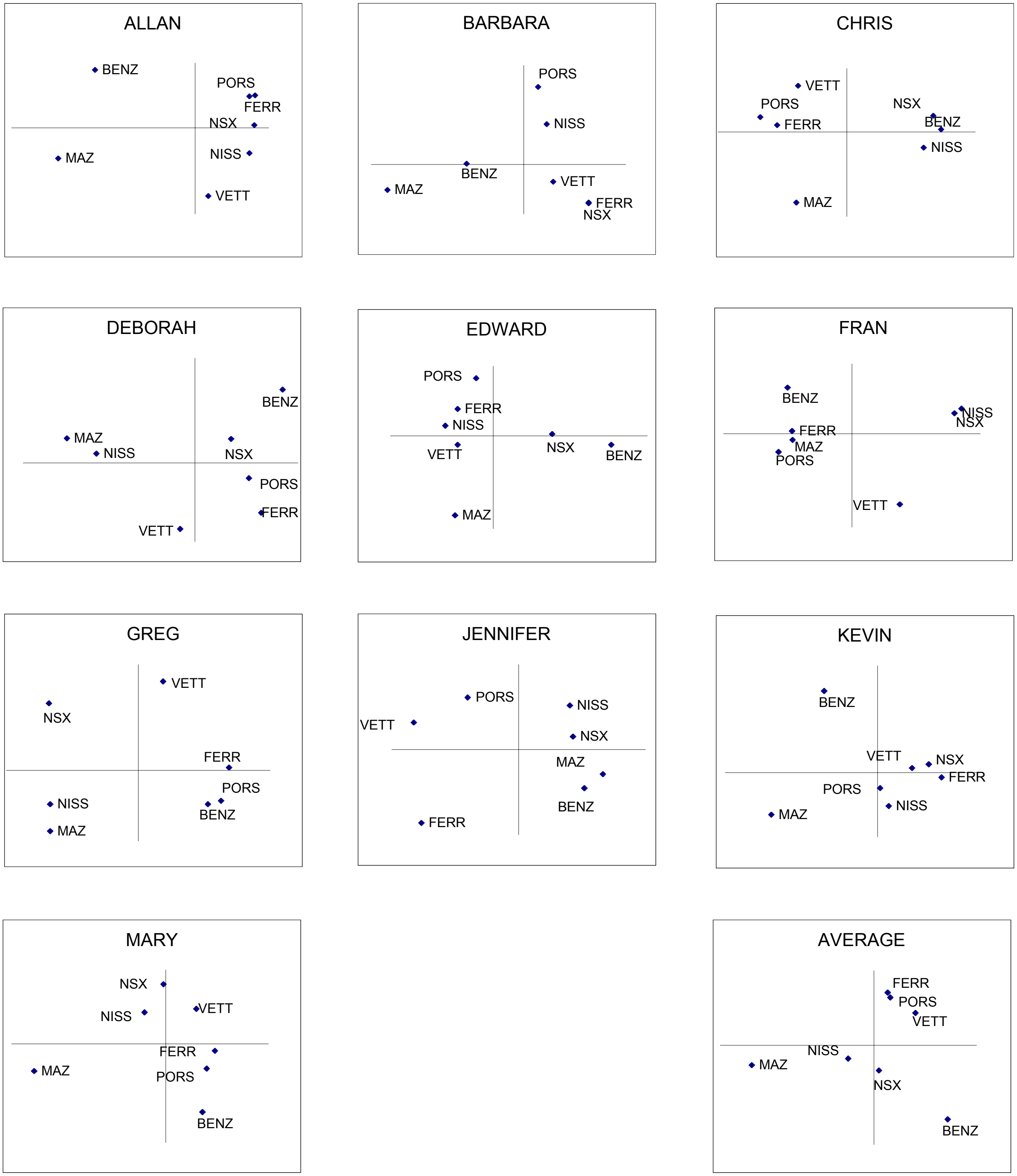
The primary benefit of this aggregate-level analysis is that it gives the brand researcher a greater ability to generalize across consumers. Network analyses can be conducted on individual networks (e.g., Figure 3) or on these aggregate networks (Figure 4). For instance, in Figure 3, we see an individual's net that shows many associations to Corvette, and this is also true in the aggregate Figure 4; that is, even after aggregating the views of several subjects, this sports car continues to elicit other brands and attributes even among a larger set of competitors. On the other hand, the respondent yielding the information in Figure 3 does not include the Miata sports car, yet this brand elicited many associations among the other respondents in Figure 4.

Figure 4. Sports Car Network



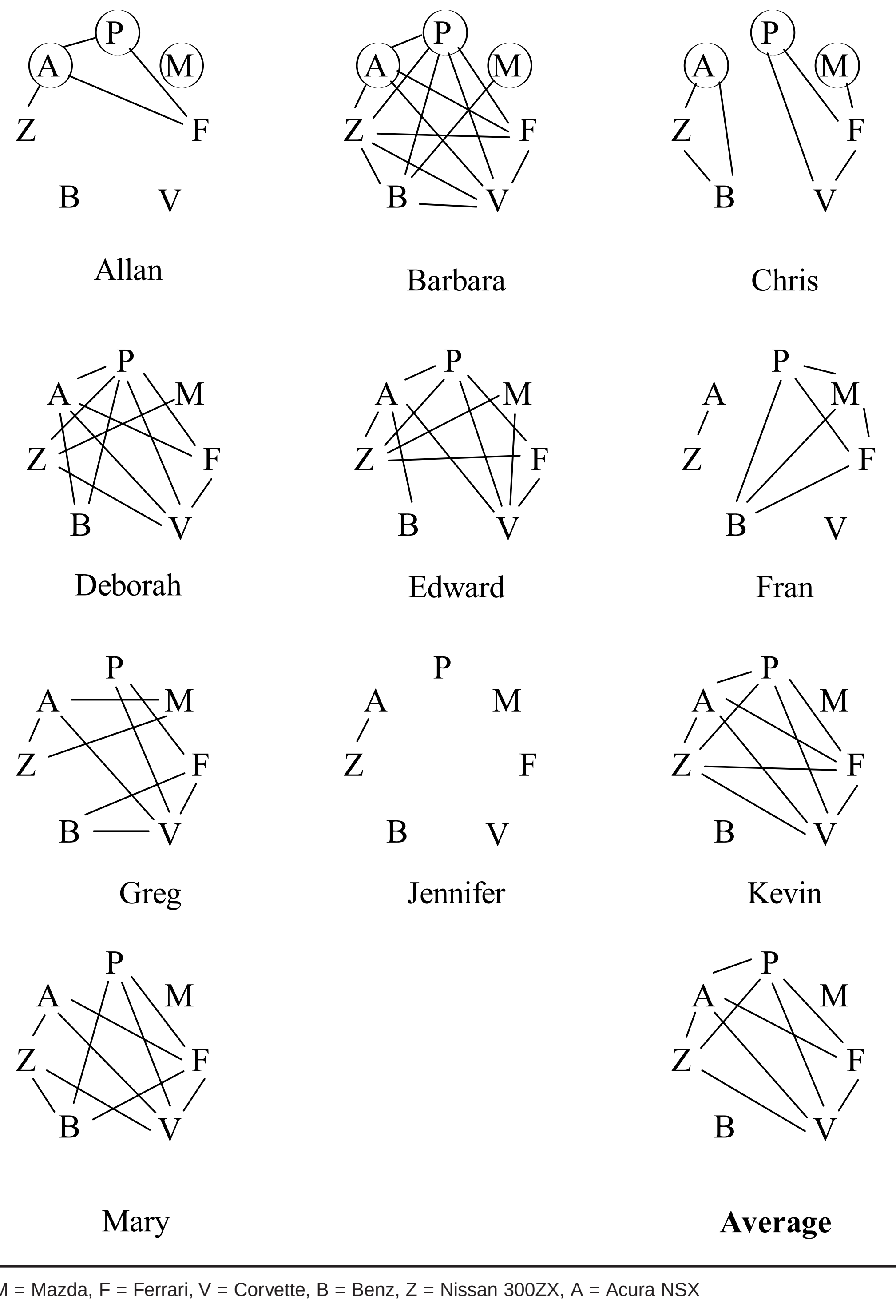
In terms of comparing MDS and networks in their aggregate forms, we have illustrations of 10 individual subjects' MDS plots, and, in the lower-right corner, the aggregate (see Figure 5). Although some aspects of the aggregate MDS plot resemble some aspects of many of the respondents, aggregation does destroy some idiosyncratic perceptions.

Figure 5. Individual MDS Plots and Aggregate



Similarly, Figure 6 contains those same 10 subjects' data modeled as networks. Again, the aggregate, obtained by the procedure just described, appears in the lower-right corner. Aspects of this network appear to resemble aspects of the individual networks. Clearly both MDS and networks function like means, in that any average is not perfectly descriptive of the component data points that constitute its whole. Means are usually paired with standard deviations to give the researcher a sense of variability that is not captured. MDS and networks are both methods that could use the development of variance description.

Figure 6. Networks from Pairwise Sports Car Data



[1] P = Porsche, M = Mazda, F = Ferrari, V = Corvette, B = Benz, Z = Nissan 300ZX, A = Acura NSX

Finally, aggregate views also allow brand researchers to segment the market based on differing consumer perceptions. The 10 network matrices represented in Figure 6 were correlated to obtain a 10 x 10 matrix of similarities among the respondents. We analyzed the matrix for subjects' equivalence, and the resulting subgroups were

{Allan, Jennifer}, {Barbara, Edward}, {Greg, Chris}. Each of these groups is essentially a market segment because of shared perceptions of brands. Allan and Jennifer had sparse networks and connections between the two Japanese cars; Barbara and Edward were grouped based on the existence of the {Corvette, Ferrari, Porsche}, {Porsche, Ferrari, Nissan}, and {Porsche, Acura, Nissan} cliques within their networks; and Greg and Chris formed a segment because of their common {Porsche, Corvette, and Ferrari} clique.

Network researchers are also often interested in using each consumer's network in a regression to predict the overall network (Krackhardt 1988). This analysis would determine if the cognitive network of one person is capable of predicting the aggregate network of the segment. These predictions appear in Table 6. The network of one of the subjects, Kevin, predicted the aggregate network very well relative to the others ($r_{(Kevin\text{-}Aggregate)} = .908$). Such a person might be a candidate "opinion leader," and could be quite helpful to future research concerning associative networks for such a segment.

Table 6. Pairwise Sports Car Study Network Measures

Subject	Prediction of Average (r)
Allan	0.560
Barbara	0.612
Chris	0.205
Deborah	0.633
Edward	0.556
Fran	0.205
Greg	0.221
Jennifer	0.259
Kevin	0.908
Mary	0.522

Figure 4 contains the empirical network for the sports car data aggregated over nine consumers. Note that it is more complex than the networks in figures 1 and 2, so the analytical network techniques described next will be extremely helpful for understanding the meaning of the structural ties in the Figure 4.

As we have stated, we use the repertory grid as our means of data collection, primarily because of its ability to bridge the gap between qualitative data collection (i.e., associations) and quantitative analysis techniques (i.e., representation). However, we do not want the researcher to feel constrained with respect to data collection. Regardless of the method by which data are collected, the network method of representation can yield insight into consumer perceptions of brands above and beyond what has currently been discussed in the marketing literature. We turn to those network methods now.

Modeling the Network Structures

There are three primary properties of network structure that we will explore in this paper.[7] These methods include measures of centrality, which are indices that offer a sense of how important each node is in the network; cohesion, which groups the nodes that are most interconnected; and equivalence, which groups the nodes according to their similarity vis à vis their connections to the other nodes. (These methods are easily accessed through available software, e.g., UCINET, [Borgatti, Everett, and Freeman 1992], or calculated using spreadsheet software that performs matrix algebra.)

Centrality. Indices of centrality are intended to uncover those nodes in the network that are particularly important and influential in the spread and activation throughout the network. Concepts (brands or attributes) that are most central to the network are a manifestation of core (i.e., central) beliefs (Loken and John 1993, p. 72). In networks, centrality measures are indices of importance that are based on the location of a node within a network relative to other nodes. In the current research, the centrality of a particular brand node, say Porsche, represents the extent to which the car is perceived to be a prototypical or representative sports car. Similarly, a highly central attribute node (e.g., "fast") would be one thought to be very characteristic of the sports car category.

There are several different types of centrality that can be measured, including degree, betweenness, and closeness centrality (Freeman 1979; Knoke and Kuklinski 1982; Wasserman and Faust 1994). Perhaps the most commonly used measure of centrality is called degree centrality, C_D. The degree of a node, C_D (sometimes called a point, p), is defined as the number of other points that have a direct tie to that node (Freeman 1979; Czepiel 1974). Degree centrality is computed as:

$$C_D(p_k) = \sum_{i=1}^{n} a(p_i, p_k)$$

where n = the number of nodes in the network

$a(p_i,p_k)$ = 1, if and only if p_i and p_k are connected by a link
0, otherwise

In essence, degree centrality measures network activity. For instance, in terms of the Peter and Olson (1993) network in Figure 2, the node Nike has the highest degree centrality, 4, because it has more direct associations than do any of the other nodes. Conversely, the node avoid-sore-knees has a degree of only 1 because of its single connection to the node feels-soft-to-run-in.

A second measure of centrality is based on betweenness, C_B, which is often thought of as a measure of control within a network. The betweenness measure is defined in terms of probabilities; since there is more than one possible path, it considers the probability of using a particular path (Freeman 1979). The formal equation for betweenness centrality is:

$$C_B(p_k) = \sum_{i}^{n} \sum_{j}^{n} b_{ij}(p_k)$$

for all $(i < j) \neq k$

and where

$$b_{ij}(p_k) = \frac{g_{ij}(p_k)}{g_{ij}}$$

where g_{ij} represents the number of geodesic paths from point *i* to point *j* and $g_{ij}(p_k)$ represents the number of geodesic paths from point *i* to point *j* that contain p_k. A geodesic is defined as the shortest path(s) between two pairs of nodes. Therefore, $b_{ij}(p_k)$ represents the probability that p_k falls on a randomly selected geodesic connecting *i* and *j*. Betweenness centrality reflects the likelihood that some node will be activated as associations spread throughout the network; if a node is on many paths between other pairs of nodes, then it is "between" many nodes and it will have a high betweenness centrality index (Freeman 1979). For example, in Figure 2, the node avoid-sore-knees is not between any pair of nodes, so has a betweenness centrality index of 0. Its adjacent node, feels-soft-to-run-in, is higher on betweenness centrality than running (in the lower-right of the figure) even though the latter has more degrees. This result is true because the only way that the node avoid-sore-knees is a part of the network is through its affiliation with feels-soft-to-run-in. Therefore, feels-soft-to-run-in is high on betweenness centrality because it controls the access of avoid-sore-knees to other nodes in the network. In contrast, while access to the node running allows direct access to the three brand nodes, those nodes each have alternate paths to the other nodes in the network. The betweenness status of running is not critical for access to the entire network.

A third type of centrality, C_C, which is based on closeness, measures exactly what its name suggests: how close a node is to other nodes (Sabidussi 1966). The index of actor centrality based on closeness is defined as:

$$C_c(p_k) = \left[\sum_{j=1}^{g} d(p_i, p_k) \right]^{-1}$$

where $d(p_i, p_k)$ is the number of lines in the geodesic linking nodes *i* and *j.*

Theoretically, closeness centrality is typically thought to represent independence from the control of other nodes in a network. In Figure 2, the nodes feels-soft-to-run-in, New Balance, Brooks, and cushioning all have only two direct links in the network. However, the latter node is closer to the majority of nodes in the network because of the denseness of connections near that cushioning node. These three primary variants of centrality measures are available (Freeman 1979; Knoke and Kuklinski 1982; Sabidussi 1966). If "centrality" is the network construct, each of the indices is a slightly different operationalization. For the network in Figure 4, however, these centralities indices are highly correlated (the average correlation is r = .7); thus, we focus on the simplest index, C_D, for illustration. As previously mentioned, C_D is the number of associations made to each node. In Figure 4, the nodes Corvette, Miata, low price, and non-European have the most associations to other brands and attributes in the net. Evidently, these particular consumers were concentrating on the domestic sports car market. The actual indices appear in Table 7.

Table 7. Centralities for Network Nodes in Figure 4

		Degree Centralities
Car Brands:	Benz	6
	Corvette	10
	Ferrari	0
	Jaguar	4
	Lamborghini	4
	Maserati	0
	Mazda RX	6
	Miata	10
	Mustang	6
	Nissan ZX	6
	Porsche	3
	Probe	0
	Viper	0
Attributes:	Classic	7
	Convertible	6
	Foreign	2
	Low Price	9
	Non-European	9
	Sporty	6

If marketing communications are intended to change consumers' perceptions regarding a brand, an attribute, or the category, it would be interesting to study how sensitive centrality indices are to attempts at modifying such associations. For example, if consumers read about a soon-to-be-introduced inexpensive sports car, we hypothesize that associations to price would change, perhaps increasing that attribute's centrality to the perceptions of the market.

Cohesion. While centrality focuses on nodes within the network (one brand or attribute at a time), network researchers are also interested in methods that identify subgroups within networks. Subgroups can be based on interlocking cohesion or the structural equivalence. We describe the different criteria for grouping together nodes via methods for detecting cohesion and equivalence.

Two brands or attributes will be located in a cohesive group if they are mutually connected (Luce and Perry 1949; Reingen et al. 1984). Cohesive cliques require that three or more nodal members be interconnected (dyads are cohesive, but groups are defined as comprising three or more nodes). These brands may be considered complements: When consumers think of one, they almost automatically think of another—as soon as one is activated, so is the other.

For the empirical network in Figure 4, the cohesive groups are found in Table 8. Most of the groups contain both brands and attributes. These associations clearly indicate the qualities of the brands that are relevant to the consumer. Not all brands are associated with all attributes. In MDS, researchers can study how the brands are perceived along each attribute, but these network groupings indicate more clearly that some attributes are simply not relevant for some brands, and that the extrapolation done routinely in MDS may be meaningless.

Table 8. Cohesive Groups for Network in Figure 4

Group[1]	Membership[2]
1	CORVETTE, MIATA, MUSTANG, NISSAN ZX, MAZDA RX, Low Price, Non-European
2	CORVETTE, BENZ, MIATA
3	CORVETTE, JAGUAR, LAMBORGHINI, BENZ, Classic
4	CORVETTE, Classic, Low Price, Non-European
5	PORSCHE, Foreign, Sporty
6	MIATA, PORSCHE, Sporty
7	MIATA, Convertible, Low Price, Non-European, Sporty
8	BENZ, MIATA, Convertible
9	Classic, Convertible, Low Price, Non-European
10	BENZ, Classic, Convertible

[1] Group order is arbitrary.

[2] Sports car brands are in capitals, attributes in upper and lower case.

The first cohesion group is dominated by the domestic market, which is perceived to be relatively less expensive than the foreign sports cars. The second group is the only group solely composed of car makes—relative to all the elicited brands and their distinguishing attributes, Corvette, Benz, and Miata are associated (e.g., convertibles). The third group delineates "classic" sports cars. The fourth group would be of particular interest to the Corvette brand manager, given that the associations isolate this single brand along with a number of perceived attributes.

Descriptions of sporty cars, particularly Porsche and Miata, comprise groups 5 through 7. Association groups 5 and 6 illustrate quite clearly that Miata is a sporty car, much like Porsche, except that it is not foreign. The seventh clique of associations comprise a very clear description of Miata: it is perceived as a low-priced, domestic, sporty convertible.

Groups 8 and 10 describe the similarity between Benz and Miata. They are both convertibles, but Benz carries the tradition of being a more classic car.

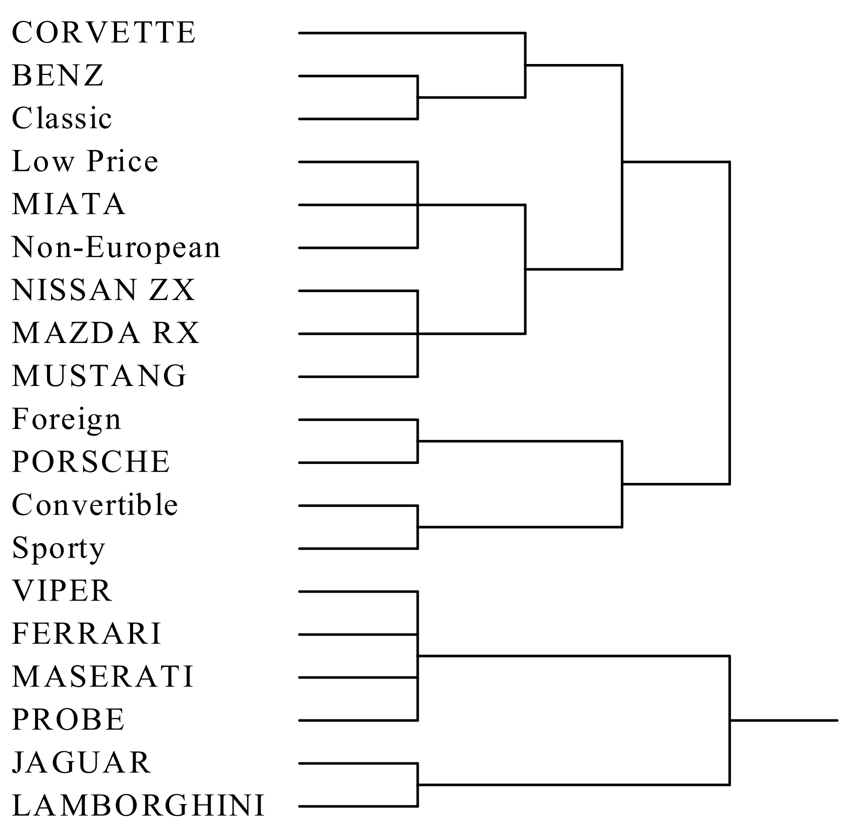
Group 9 is the only set of nodes that is all attributes. The attributes comprise the basic features of sports cars for this particular sample (of respondents and sports cars). These category descriptors are qualities that are closely linked—the activation of one brings another to mind quickly.

Each of the groups is meaningful in its own way. The brand managers of these cars would be especially interested in the groups that contain the brand for which they are responsible, as well as brands and attributes they wish to emulate. Here, marketing mix variables are intended to change consumers' associations—to change the group of associations linked to the focal brand.

Equivalence. Where cohesive groups are defined on nodes that are connected, groups of nodes that have equivalent associations are based on similarity (and they may or may not be connected). They are interchangeable in the network structure because they occupy the same structural space—they are connected by the same set of ties with the rest of the network. In essence, structurally similar or equivalent nodes are substitutes, which we will explore in relation to diagnosing branding effects of cannibalization and brand parity later in the paper.

Table 9 contains the hierarchical sets of nodes in their equivalence groups. It is particularly informative when brands cluster with attributes, e.g., Benz and classic, Miata and low price and non-European, Porsche and foreign. These brands are apparently interchangeable with the stated attributes—when the consumer thinks "Miata," they could just as easily have thought "low price."

Table 9. Equivalence Groups of Nodes Occupying the Same Position from Figure 4



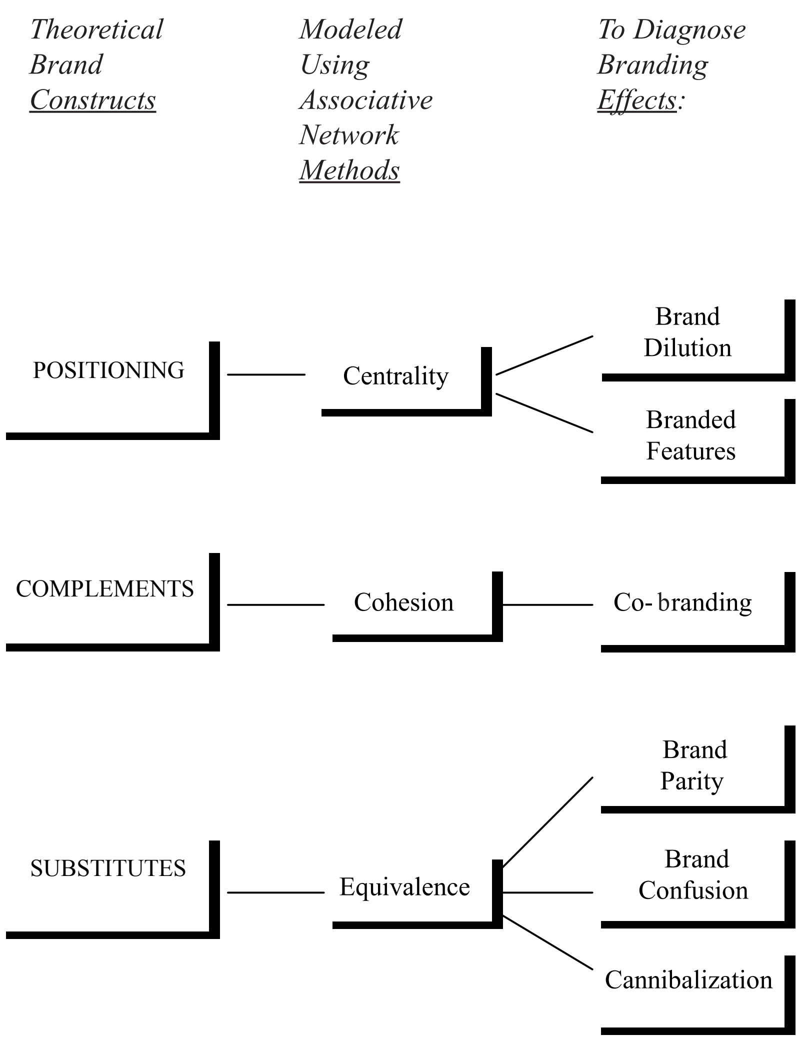
Groups that contain multiple brands indicate those brands that should be suspected of being extremely interchangeable in the mind of the consumer; by definition they have equivalent structural ties in the associative network—one brand has the same associations as another in its group. Such groups include {Nissan ZX, Mazda RX, Mustang}, {Viper, Maserati, Ferarri, Probe}, and {Jaguar, Lamborghini}. Given that the consumer associations to one brand in a group are identical to the associations elicited by another, the consumer in the market for a Nissan ZX may be more easily swayed to purchase a Mustang instead, at least relative to a nonequivalent brand like Porsche.

Finally, one group consisted of two attributes, convertible and sporty, which suggests these concepts are interchangeable, or even redundant, in the mind of the consumer. Note, too, that as with any hierarchical structure, as one proceeds up the tree, fewer, larger groups indicate those associations that also exist but are less strong than the initial group compositions (e.g., the addition of Corvette to the Benz, classic cluster).

Diagnosing Branding Effects

With these brief overviews of MDS and associative networks as background, we now turn to substantive concerns regarding branding phenomena. We seek to understand three branding constructs that manifest themselves in a variety of branding effects. These brand constructs are "positioning," "complementarity," and "substitutability." The first of these focuses on a particular brand (relative to others) whereas the latter two focus on relationships between brands. We describe each construct and the methods by which each could be studied. Figure 7 presents the relationships between branding constructs, observable branding effects, and network methods currently discussed.

Figure 7. Branding Constructs, Branding Effects, and Associative Network Methods



Brand Positioning

Brand positioning is perhaps that activity best known to brand managers. A brand is positioned as having more good attributes and fewer poor attributes relative to the other competitive market offerings. If a brand has a particularly strong and favorable heritage, the manager may consider leveraging those positive associations by introducing a brand extension. The positive associations consumers hold for the parent brand are thought to transfer to the new introduction by the activation of the original brand name. Two brand positioning phenomena enjoying current popularity are “brand dilution” and the “branding of features.”

Brand Dilution. A brand phenomenon of some concern recently, brand dilution is the extent to which capitalizing on brand associations (e.g., by introducing brand extensions) may harm the original brand. The brand manager asks, “Is my brand’s equity in jeopardy of being diluted if we introduce a brand or line extension that is not congruent with my existing brand image and positioning?” Advertisers wish to clarify a brand’s position in order to maintain a brand’s equity (Loken and John 1993; Dacin and Smith 1994). Brand dilution would be demonstrated most pointedly by a decrease in positive associations, or an increase in negative associations, with the focal brand. However, the category itself may be diluted (e.g., as when the centralities for positive attribute nodes decrease, or those for negative attributes increase).

Branded Features. Attributes closely associated with the host brand are candidates to be further branded and differentiated themselves. Doing so would yield a “branded feature.” To this end, brand managers ask, “What features of my brand do consumers perceive to be the most important?” “And what attributes are so central to my brand that they are pivotal to the overall image of the brand?”

Candidates for branded features would be those attributes high on centrality—those that are important to the brand and category. For instance, in Figure 2, the concept of cushioning is a node high on centrality, so it would make sense to consider it as a candidate for a branded feature. It is also most closely associated with Nike, and, of course, the branded feature Nike-Air capitalizes on the centrality of cushioning to the overall image of Nike products.

For both brand dilution and branded features, we would expect traditional MDS methods to be fairly diagnostic. The brand manager would examine the perceptual maps looking for changes in location of the parent brand, and the character of the location of the newly introduced brand (e.g., is it near other brands and attributes with desirable qualities?). We would also expect that network methods could detect changes in cognitive associations regarding the parent brand. In particular, centrality indices may be used to verify that the links to the focal brand are still positive and active. Thus, we expect both MDS and associative network methods to be useful to the brand manager seeking to diagnose circumstances of brand dilution or potential features to brand.

Complementary Brands

The next two branding constructs consider brands together. Complementarity capitalizes on the associations between brands, seeking, for example, opportunities for co-branding.

Co-branding. Co-branding effects include the use of ingredient brands or composite brands. Ingredient brands can be used as a portion of some product (e.g., an Intel Pentium Chip inside an IBM ThinkPad Notebook Computer, Starbucks coffee served aboard United Airlines flights), whereas composite brands are the "bundling of two brands to provide an enhanced consumer benefit or reduced cost" (e.g., Microsoft and General Electric's MSNBC Cable/Internet offering [Aaker 1996, p. 299]). The brand manager asks, "What brands might be good candidates for co-branding?"

Cohesion associative network methods offer empirical possibilities for co-branding. Groups of attributes and brands defined on their mutually connected associations would be fitting candidates for opportunities to incorporate multiple brands. These groups reflect structures of a natural complementarity of the products that already exists in the consumer mind.

In MDS, researchers would seek brands that were close in space, i.e., perceived to be highly similar. However, this exercise will not prove to be terribly diagnostic, as we shall demonstrate.

Substitutable Brands

Substitutable brands, like complements, are brands (and attributes) that go together by some criterion. However, while complements are brands that the manager seeks to package together, substitutes are similar brands that consumers alternatively purchase in opposition (Aaker and Keller 1990, p. 38). Substitutability includes a number of highly competitive problems, including brand parity, brand confusion, and cannibalization.

Brand Parity. Brand parity is the consumer perception of sameness among brands. When describing the brands' market equivalences in Figure 4's network, we identify the owner of a Nissan ZX as a consumer who may be persuaded to purchase a Mustang. There is perceived brand parity between Nissan ZX and Mustang. This knowledge would allow brand managers of the nonincumbent brands to market more effectively to that driver, and hence influence alternative car purchase. The brand manager can more readily identify potential customers and gain more precise information about the competition—using the voice of the customer instead of management or "market structure."

Brand Confusion. Presumably, brand parity taken to an extreme yields brand confusion. The brands are indistinguishable, commodity-like, and the stimulation of one brand may elicit consumer associations relating to the other brand.

Issues of brand confusion have been raised recently in the marketing literature, and they can be so serious that they require legal settlement (Zaichkowsky 1995;

Kapferer 1995). Brand confusion is clearly not desirable for the market leader, but may well be an intended strategy for a me-too brand.

Cannibalization. Cannibalization occurs when one of a firm's brands steals market share away from another. In a sense, this branding effect is like brand confusion within the same manufacturer—the products being cannibalized are in-house functional substitutes from the consumer's point of view.

In the network in Figure 1, "Big Mac" and "hamburger" are structural substitutes. Their equivalence indicates that McDonald's should be concerned about cannibalization. This substitutability suggests that a consumer ordering one is as likely instead to order the other because of their perceived similarity in the associative network structure. In particular, the "Big Mac" brand manager should be working to form associations in the consumer mind to distinguish it from McDonald's more generic hamburger offerings (e.g., "the Big Mac—it's more than a hamburger").

In terms of empirical analysis, MDS would be looking for brand substitutes (brand parity, brand confusion, cannibalization) by identifying those brands that were perceived to be similar enough to be substituted. However, note that the criterion of "similarity," the basis of MDS models, is the same criterion the researcher would use to understand "complementary" brands. In an MDS plot, two brands occupying locations close in space could not be distinguished as either brands that were potentials for complementarity or brands that would compete on market share. Complementarity would be a force that drew two brands together (IBM, Intel), whereas substitutability would be a repelling force between two brands close in space (Pepsi, Coke). MDS is a multivariate method that cannot distinguish between these two classes of branding phenomena.

In contrast, associative network methods apply cohesion techniques to seek patterns of connectedness for complementarity, and network equivalence techniques to seek similar structures for substitutability. Complementarity is defined by associations among brands and attributes (e.g., IBM is linked to Intel). Substitutability is detected by similarities between interconnections shared by brands and attributes (e.g., Pepsi and Coke have similar links to other brands and attributes).

The Branding Experiment

In this final section we describe an experiment in which we attempted to manipulate brand associations through mock advertising campaigns. We explore the effect of the different brand extensions in the resultant brand associations and perceptions in a pre- / post-design for both the MDS and associative network methodologies.

The experiment was a 3 x 2 x 2 design. Subjects saw an advertisement for one of three types of brand extensions. They provided data either in an MDS or repertory grid format. They completed the data task before and after being exposed to the brand extension intervention. Subjects were graduate students in marketing. The total sample size was 102.

We advertised the Porsche sports car manufacturer as introducing one of three types of brand extensions: For 36 subjects, "Model X" was described as an economy car, featuring low price and good mileage. For 33 subjects, "Model X" was a family car with features relating to the safety and comfort of a family of five (e.g., enlarged trunk space, built-in child seats, airbags, four-wheel drive, luggage racks). Finally, 33 subjects served as a control group who was told the "Model X" was "everything you ever thought a Porsche to be" with no new attributes featured.[8]

The second experimental factor was the data elicitation/representation technique. In the MDS condition, 57 subjects provided pairwise similarities judgments on seven sports cars: Acura NSX, Chevrolet Cavalier, Ferrari, Mazda Miata, Mercedes 300SL, Nissan 300ZX, and Porsche (selected by pretesting as typical brands). Subjects rated the cars on the price, quality, sportiness, convertibility, foreign, stylishness, and performance. In the associative network condition, 45 subjects named (up to) seven sports car brands, and they compared the brands via triadic elicitation.

The third factor was a straightforward pretest, posttest repeated measures assessment. Subjects completed their data collection task (either MDS or repertory grid) prior to and following the brand extension intervention.

A multimedia campaign was used to try to enhance external validity or at least credibility. The new Porsche was announced through word-of-mouth (a conversation excerpt), concept board (a print ad), expert reviews (*Consumer Reports*), and a news report (mock article on the first page of the *Wall Street Journal*). All these forms of communication were used to ensure that the message of the new product introduction was "heard." We were not concerned with differentiating the ad sources, but rather with creating an intervention with a strong impact (e.g., heavy ad weight). A strong manipulation would give either method, MDS or networks, a fair chance to detect changes in consumer associations. We examine the MDS results first, followed by associative networks.

MDS Results

Figures 8, 9, and 10 contain the results for the pre- and post-MDS solutions for the economy, family, and regular Porsche conditions (from the INDSCAL model [Carroll and Chang 1970]). The pre-proximities were judgments made among seven sports cars. The post-proximities data also contained the eighth stimulus of "Model X." The plots display the stimulus coordinates and the fitted attribute vectors.

Figure 8. Pre- and Post-MDS Solutions for the Economy Model X by Porsche

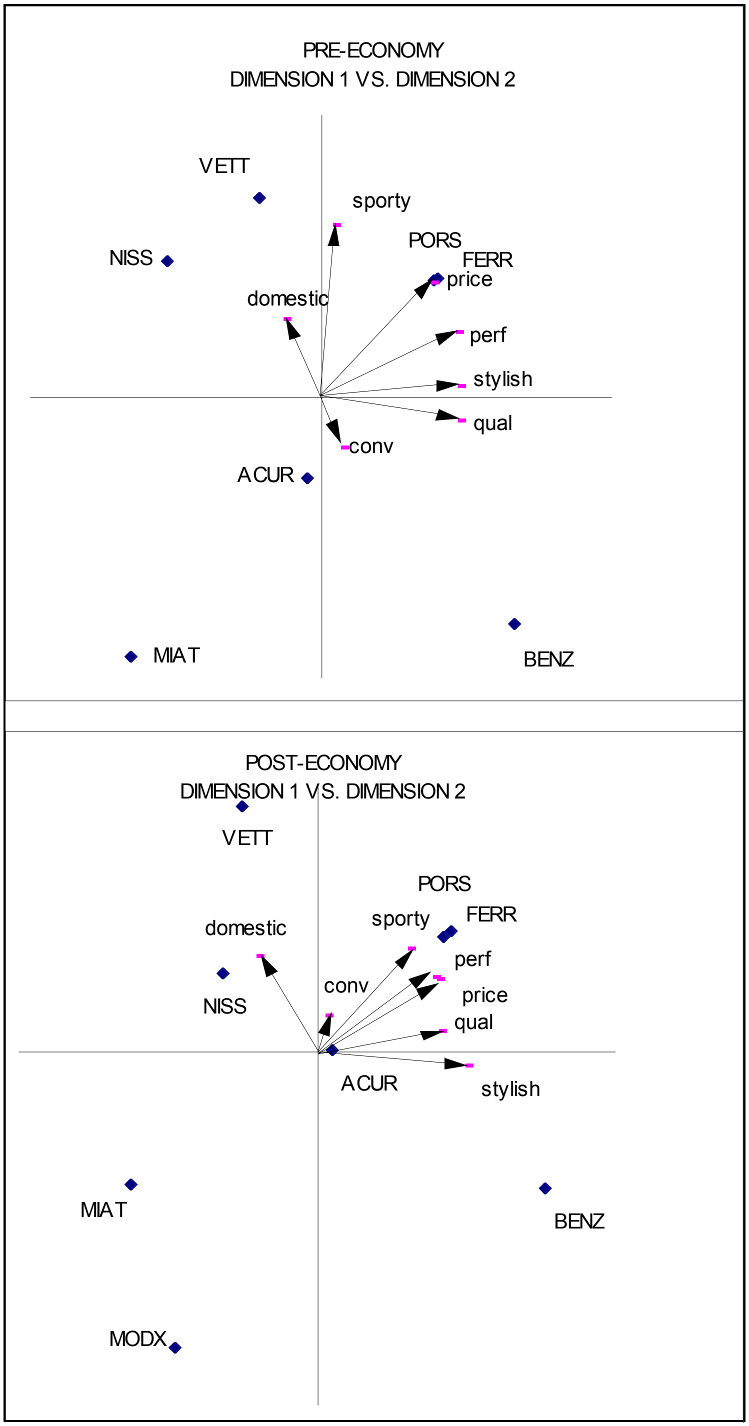


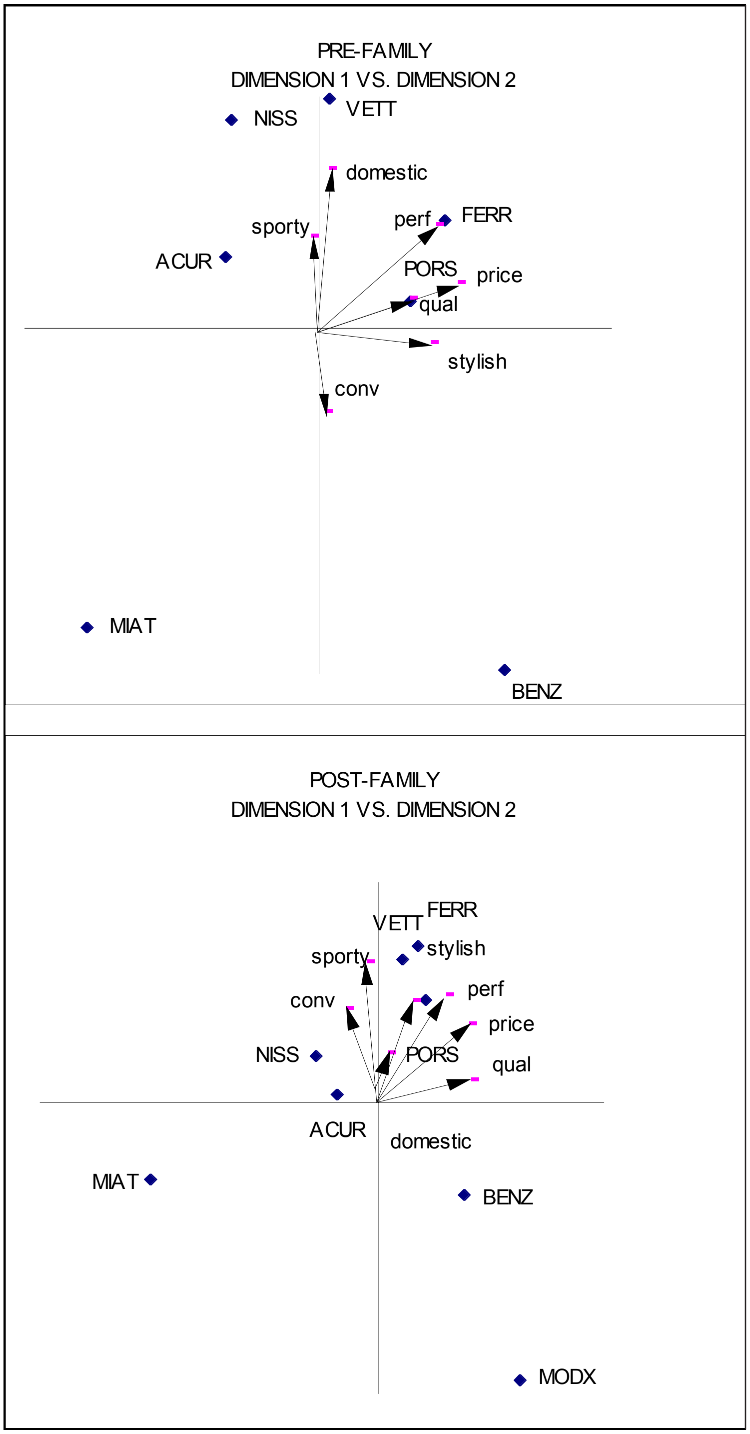
Figure 8 displays the results for the "economy Model X." The first quality to note is that the MDS plots are fairly stable from pretest to posttest, both in the relative placements of the brands themselves, and in the rough orientation of the attribute vectors in space. For example, Nissan and Corvette occupy the upper-left quadrant, Porsche and Ferrari the upper-right, and Benz is by itself in the lower-right of the plot.[9] The vectors span clockwise from "domestic" at the upper-left, to "sporty, price, and performance," and to "quality and stylish." This stability is important: If perceptions changed dramatically, the brand manager would not know whether to attribute the change to truly having affected the entire category of brand associations for sports cars or to random error. These plots are fairly reliable, so we can look for changes in Porsche and Porsche's Model X.

Note that if we were concerned that the introduction of an "economy Porsche" would dilute the parent Porsche, we would leave these plots unconcerned. The original Porsche brand remains in its location near Ferarri in the post-plot, described by such attributes as high performance, sporty, and high priced. The Model X appears in the post-plot in a sensible place—as a mirror image to its parent brand Porsche in the space (in the lower-left quadrant) and opposite most of the desirable attributes (less sporty, less performance is expected, less costly, lower quality, etc.). If any association seems to have shifted, it is to the parent Porsche, which is perceived as somewhat sportier in the presence of the economy model.

Thus, brand dilution does not seem to have occurred for Porsche, though the new introduction Model X is not highly regarded. In addition, these maps suggest that "sportiness" and "performance" are particularly strong candidates for branded features (e.g., perhaps the "Indy Porsche" or the "Porsche engineered motors").

Figure 9 displays the results for the "family Porsche." Again, note that the brand stimuli are fairly stable: Miata in the lower-left; Acura and Nissan near the upper-left; Corvette near the top; Porsche and Ferrari at the upper-right; and Benz isolated at the lower-right. Porsche's hypothetical new Model X is in a location in the post-plot that makes sense, defending the clarity of the MDS methodology—the Model X, which is said to be roomier and built for the family, is now located nearer the Benz, which is thought to be less of a sporty car and more sedan, or family-like.

Figure 9. Pre- and Post-MDS Solutions for the Family Model X by Porsche



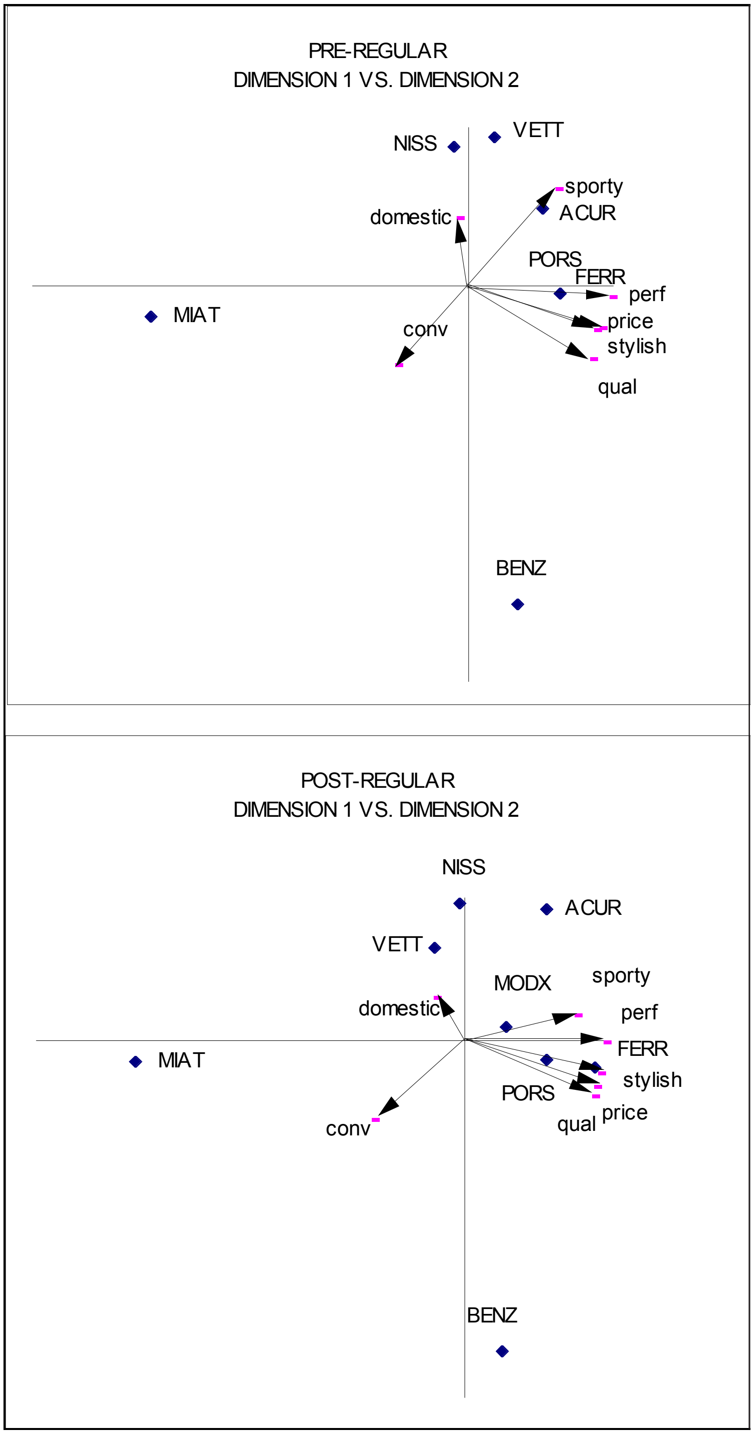
In these MDS plots, we see slight shifting in the attribute vectors, suggesting a reformation in consumer perception of the qualities that go together and describe the sports car category, once a family-oriented Porsche is assimilated. The property of convertibility swings altogether from a "southern" direction, describing Miata and Benz, to a "northern" direction, given that it is not evidently thought to be descriptive of a family Porsche.

Similarly, the "domestic" attribute changes from a "northern" pointing vector that is long, which indicates its utility in describing space, to a miniscule vector near the origin in the post-plot, indicating that it is no longer a particularly useful attribute for distinguishing among these sports car brands. Evidently the concept of a family Porsche is peculiar enough to modify the brand associations to the category.

Finally, the location of the "stylish" attribute vector has also shifted somewhat. The parent Porsche is enhanced in stylish associations, in contrast to the Model X, which is not expected to be particularly stylish whatsoever.

Figure 10 contains the representation of the "regular Porsche." Given that this condition is essentially a control group, we would expect to see very little movement from the pre- to post-plots. And indeed, there is fairly strong stability. The only possible exceptions include a little bit of movement and reversals among the {Nissan, Corvette, Acura} cluster, and a slightly clockwise rotation of the "sportiness" vector. Note that the location of the new Model X is sensible—right near its parent brand.

Figure 10. Pre- and Post-MDS Solutions for the Regular Model X by Porsche



Overall, we might conclude that MDS showed admirable qualities. The stimuli and attribute vectors that should have remained stable were indeed relatively stable. Indeed, we might query whether MDS results might tend to be too stable and not sufficiently sensitive to communications interventions, but we have no reason to critique the method without more data. In particular, the new Model X was located in a sensible place in each of the three conditions.

It did not appear that brand dilution was a problem for these consumers: In both of the brand extensions (economy and family), the original Porsche seemed to have benefited from the contrast. But for other data or in other purchase categories, brand dilution could have occurred. In particular, these plots demonstrated the ease with which an MDS study could be executed, and the results indicated the method's relative sensitivity to the "brand positioning" construct, and its manifest possibilities in the branding effects of "brand dilution" and "branded features."

In terms of the brand constructs of "complementarity" or "substitutability," our previous logical argument should now be clearer in the presence of data—that two brands located close in space cannot be distinguished as complements or substitutes (e.g., in most of the plots, Porsche and Ferrari were brands that occupied locations close in space). Their small interpoint distance is not distinctively diagnostic as to whether consumers activate one brand when hearing another, so that the firms may consider complementarity co-branding scenarios, or whether consumers see the brands as similar and interchangeable substitutes, therefore competing with one another.

Presumably, additional data could tease apart these cases, but on the basis of the MDS information alone—the distance-based model's fit distances—two brands are located together if they are similar. Closeness may be translated as complements or substitutes, depending on the situation. In the associative network methods, these very distinct branding phenomena will be easily differentiated.

Associative Network Results

Each respondent generated a list of cars and proceeded through the triadic comparisons. A repertory grid matrix was generated for each subject. Each of the subjects matrices consisted of between 1 and 8 attributes and between three to seven cars, depending on how many each subject listed. A content analysis determined a common set of 29 attributes across all respondents, which was considerably larger and more expansive, and, hence, more informative and subject-derived, than the 7 different attributes provided in the MDS condition.

Similarly, 28 vehicles were elicited, four times as large as the list provided in the researcher-determined MDS condition, and far more than could be rated in an MDS proximities task. For the purpose of illustration, these lists were parsed down further to 12 cars and 16 attributes based on the agreement of at least 4 of the 45 respondents (10 percent of the sample).[10]

We proceed through the associative network results, beginning first with the centralities for the nodes in each of the three brand extension conditions. We then present the cohesion cliques and the equivalence sets of substitutes.

Centralities. Table 10 contains the degree centralities prior to and following the interventions announcing each of the three brand extensions. Few significant changes resulted from the advertising communications intervention. When significantly fewer associations were made after the manipulation, decreases are marked by minus signs; significant increases have plus signs.

In the economy condition, fewer associations to "slower" and to "Jaguar" were activated. The attribute "slower" may have been less relevant when the consumers were asked to focus on costs, and Jaguar may have been activated less because a cheap Porsche does not yield visions of an expensive Jaguar. The Model X had more associations in the post-conditions than in the pre-conditions, primarily because it did not exist in the pre-conditions. Nevertheless, the post-centralities were of substantial sizes, indicating that the respondents were indeed thinking about the newly proposed car model.

Table 10. Pre- and Post-degree Centralities for All Three Brand Extensions

Condition:	Economy		Family		Regular	
	Pre-	Post-	Pre-	Post-	Pre-	Post-
British-Not	0	0	0	0	0	6
Classy-Less	1	1	0	0	8	0-
Common-Unique	17	11	2	5	10	12
Euro-Japan	8	9	5	8	5	4
Fast-Slower	9	2-*	5	2	5	4
Foreign-US	6	10	6	7	5	6
German-Japan	0	0	0	0	6	4
High-Low Price	9	8	8	3-	10	9
High-Low Quality	0	3	0	0	0	6
High-Low Status	6	0	6	0-	5	3
Japan-Not Japan	0	5	0	4	0	0
Less-Variety	7	5	7	6	2	6
Mature-Young Appeal	6	0	5	0-	0	0
Sporty-Variety	0	5	0	5+	0	0
Terrain-Two WD	0	6	0	6+	0	0
Sedan-Sporty	0	6	0	4	0	2
Alfa	6	7	5	6	2	0
Benz	14	8	6	3	10	11
Chrysler	0	6	0	6+	0	0
Ferrari	5	7	4	5	3	3
Jaguar	11	4-	7	4	5	2
Jeep	6	10	6	7	7	8
Lamborghini	4	2	1	1	5	4
Lexus	0	0	0	0	10	4
Mazda	7	8	6	3	8	7
Porsche	10	7	8	7	8	12
Corvette	7	1	2	4	0	0
Porsche Model X	0	9+	0	7+	0	9+

* The increases (+) and decreases (-) marked are those that exceeded 1.98 times the average standard deviation of the pre- and post-conditions within each brand extension condition. For "economy" and "regular," the difference had to exceed 7 to be significant. For "family," a difference of 5 was significant ($s_{economy}$ = 3.64, s_{family} = 2.49, $s_{regular}$ = 3.31).

For Porsche's Model X family car, fewer associations were made to "low price," "low status," and "younger appeal," whereas the nodes of "variety," "two-wheel drive," and "Chrysler" were activated more frequently. The family car brand extension was described with more adjectives than the economy model had been; hence, it is a sensible finding that we effectively created a more dramatic change for the family car condition.

In the regular Porsche condition, fewer associations to "less classic" were made. There is no particular reason why any associations should vary significantly in what is essentially a control condition. Out of 27 nodes, one centrality was significantly different, so this finding is probably due to a type I error. Only one more degree changed radically in the "economy" condition, and several more changed in the "family" condition. The number of significant changes might even be proxies for manipulation strength (effect size). Overall, these centralities, like the MDS plots, appear to be fairly stable, but the family Porsche seemed to affect respondents' associations more substantially.

Complementarity (Cliques) and Substitutability (Equivalence)

In this section, we present the network findings from the pre/post experimental design for all three brand extensions. We begin by describing the brands that are cohesive (associated), and then proceed to examine those that are equivalent (similar).

Cohesion Cliques. Table 11 contains the results on the cliques that formed in the consumer association networks prior to and following the brand extension manipulations. The 10 cliques for Figure 4 (in Table 8) were complicated enough, but the cliques that follow are based on a much larger dataset. Thus, the results are fairly complex, so they are worth explaining here.

Table 11. Cohesion Cliques of Associations

	Pre-economy Condition	Post-economy Condition
1)	Benz Jaguar Mazda Porsche	Benz Ferrari Jeep Mazda Porsche
2)	Benz Jaguar Mazda classic	Benz Ferrari Jeep Porsche ModelX
3)	Benz Jaguar Corvette	Benz Ferrari less-variety
4)	Benz Jaguar less-variety	Benz Ferrari sedan
5)	Benz Jeep Porsche	Benz non-Japanese less-variety
6)	Benz Jeep classic	Benz non-Japanese sedan
7)	Benz Jeep faster	Jeep Lamborghini Mazda
8)	Benz European/German faster	common European/German foreign high-price less-variety
9)	Benz Mazda faster	common European/German foreign sedan
10)	Benz faster less-variety	common high-quality less-variety
11)	Benz faster sporty	common high-quality sedan
12)	Benz Porsche sporty	
13)	Ferrari Jeep faster	
14)	Ferrari Mazda faster	
15)	Ferrari faster less-variety	
16)	Ferrari faster sporty	
17)	Ferrari Jaguar Mazda	
18)	Ferrari Jaguar less-variety	
19)	common faster high-price less-variety	
20)	Jeep common faster	
21)	Mazda common faster	
22)	common faster sporty	
23)	Jaguar Mazda classic common	
24)	Jaguar common less-variety	
25)	Jeep classic common	
26)	Mazda common foreign	
27)	common foreign less-variety	
28)	European/German faster high-price	
Pre-family Condition		**Post-family Condition**
1)	Jaguar Mazda Porsche	no cliques formed
2)	Jaguar Mazda classic	
3)	Jaguar Mazda common	
4)	Mazda common foreign	
5)	Benz Jeep classic	
6)	faster high-price less-variety	
Pre-regular Condition		**Post-regular Condition**
1)	Benz Lexus Mazda common	Benz Lexus Porsche
2)	Benz Mazda common non-Japanese	Benz Mazda Porsche
3)	Benz common non-Japanese	Benz Jeep Porsche
4)	Benz Jeep common	Benz Porsche sedan
5)	Benz Lexus less-variety	Benz Lamborghini less-variety
6)	Alfa Mazda common	Benz Lamborghini sedan
7)	Alfa Jeep common	Benz Mazda less-variety
8)	Ferrari Mazda Japanese	Mazda common less-variety
9)	Jaguar Mazda Japanese	Ferrari Mazda less-variety
10)	Lamborghini Mazda non-Japanese	Mazda common non-Japanese less-variety
11)	Lexus Mazda common foreign	Mazda common foreign less-variety
12)	Lexus foreign less-variety	common high-price less-variety
13)	common non-Japanese high-price	common high-quality less-variety
14)		Lexus common foreign
15)		Lamborghini high-price less-variety
16)		Lamborghini high-price sporty

A first observation is that for the true brand extensions (economy and family), the number of cliques decreased from pre- to post-manipulation. This finding suggests that the information in the communication became the focus of the consumer perception—the marketing intervention clarified and simplified the associative network (at least in the short term). The number of cliques remained approximately the same in the regular (control) condition, and, if anything, increased slightly, as if subjects were elaborating on their own individual thoughts when given no truly new information.

Note also that not all nodes, brands and attributes, appear in the cliques. Those that are absent may share plenty of dyadic associations, but they are not integrally connected with two or more other nodes that are themselves also interconnected.

To look at the content of the connections, we begin by examining the pre-economy condition's cliques 1 through 4. We see associations between Benz and Jaguar four times, clearly an indication of a strong linkage in the minds of these consumers. In addition, Mazda joins this group twice, and Corvette and Porsche are each activated once, indicating peripheral brands to the core Benz-Jaguar associative link. In the second clique are less traditional cars—the Mazda in particular is a newer entrant to the sports car category. The fourth clique suggests the perception that Benz and Jaguar are manufacturers of a fuller line, a variety of cars, not just the sports cars being considered and compared to Porsche.

We can summarize these cliques, looking for the qualities they have in common, analogous to factoring the cliques for their common and unique associations. Cliques 1-4 identify a core set of {Benz, Jaguar, Mazda} associations. Cliques 5-7 contain Benz, Jeep, and to a lesser extent, the attributes of classic and faster. Cliques 8-12 describe the Benz as fast and sporty. Cliques 13-18 primarily have the brand Ferrari and the attribute fast in common. Cliques 20-28 describe both Jeeps and Mazdas as fast sports cars with common shapes.

After describing a cheap Porsche in this economy condition, the clique structure changes quite a bit. The Benz-Jaguar connection is no longer as important, or at least it is activated less frequently. Instead, cliques 1-4 show a connection between the brands: Benz, Ferrari, Jeep, and the regular Porsche and its new Model X. Cliques 5 and 6 classify Benz and non-Japanese together—a focus on European makes. Similarly cliques 8 and 9 contrast European/German with American, together with the attribute of common shape. Finally, cliques 10 and 11 describe that common shape as associated with perceptions of high quality.

In the family Porsche conditions, prior to the marketing campaign, cliques 1-4 indicate a connection between Jaguar and Mazda and the quality of common shape. Clique 5 connects Benz and Jeep with classic, and clique 6 shows the activations among the attributes: faster, high-price, and less-variety (a high-end focused product line).

No cliques were found after the intervention. The family Porsche was described with a large number of qualities that were indeed difficult to reconcile with the status of a sports car, including leg room, full seating capacity, trunks, and bike racks etc., so perhaps the communication sufficiently confused the consumers that they had not yet had time to reconvene sensible associations. Recall the centrality results, that many changed associations were occurring in the minds of these consumers. Evidently dyadic associations were being formed and destroyed, but, as yet, cliques (groups of three or more nodes) had not yet firmed up. At this point, when "sports car" was activated, it now brought along many weird new associations, none of which had yet been strongly assimilated into the sports car category; hence yielding no cliqued associations.

For the regular Porsche condition, cliques 1-5 show similarity to the associations in the pre-conditions of the other cells (i.e., Benz and Mazda and common shape were associated). Cliques 6 and 7 emphasize the uniqueness of the Alfa Romeo. Cliques 8-10 characterize the Mazda as a Japanese make, and cliques 11 and 12 associate Lexus and non-American.

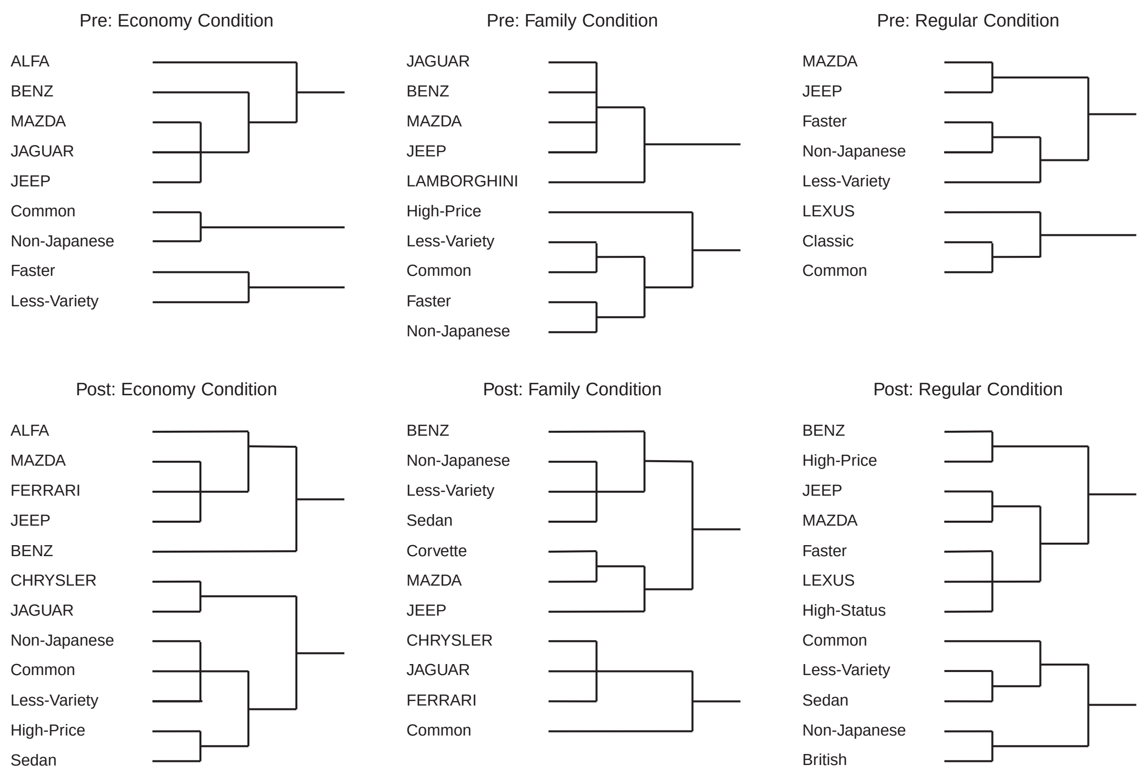
After consumers were prompted to think about Porsches, but without receiving any new attributes about the brand, cliques looked only somewhat different. Cliques 1-6 connect Benz to Porsche and, to a lesser extent, Lamborghini and sedans. Cliques 7-13 describe the Mazda as a car with common shape made by a manufacturer that produces a small variety of cars. Lastly, the cliques 16 and 17 connect the Lamborghini and high-price nodes.

The findings on these various cliques are somewhat understandable, and yet they do have some odd qualities. One finding is that the cliques differ a bit in the pre-manipulation states. Prior to being exposed to any advertisements claiming a new Porsche, the consumers in all three brand extension conditions should essentially be carrying around a somewhat similar associative network of the sporting car industry. Yet the pre-manipulation cliques suggest that the starting points for the three groups was different.

We might attribute these differences to the sensitivity of the method of data collection, in that it is essentially a free association task. Or perhaps we were too liberal in our threshold in aggregating the data, allowing more idiosyncratic voices to speak, rather than looking for a simpler majority consensus. Nevertheless, academic researchers rarely run pre- / post-designs, and perhaps it would be a more frequent finding to see subjects starting from a different perceptual place. Subjects had been randomly assigned, so we must assume that the "true" perception of the sports car industry is some composite of the three sets of findings on the pre-conditions. However, we have documented the pre-conditions, so when we compare the postintervention cliques, we can effectively "co-vary out" the prestarting point.

Equivalence Substitutes. Table 12 contains the equivalence groupings for these six conditions. Where the number of cliques usually got smaller postintervention, the number of nodes regarded as similar increased somewhat pre- to postintervention. The brands and attributes that do not specifically appear in these charts are those that form one larger group, similar in structure by default by not being highly interconnected to other network nodes.

Table 12. Equivalence of Groups of Competitive Substitutes



In the pre-economy condition, Mazda, Jaguar, and Jeep were perceived to be the most similar interchangeable brands. The attributes of non-Japanese and common shape were seen as similar (e.g., presumably the European sedan bodies). Less-variety and faster were also attributes that factored together as similar, which is also sensible given that several auto manufacturers were included in the network with specialties in sports cars.

After introducing the inexpensive Porsche, the brands and attributes perceived to be similar change somewhat. Mazda and Jeep are now grouped with Ferrari. Jaguar is grouped with Chrysler. The attributes of non-Japanese and common shape still correlate, and now less-variety joins the cluster. Finally, sedan bodies are seen to be similar to the quality of high-price.

In the family equivalence groups, there are again similarities among Jaguar, Benz, Mazda, and Jeep. There are also similarities between the attributes of less-variety and common shape, and non-Japanese and fast.

After the introduction of a big, bulky family Porsche, respondents cluster together {non-Japanese, less-variety, sedan}, {Corvette, Mazda}, and {Chrysler, Jaguar, Ferrari}. The consumer associations have been affected, but there is nothing in particular in this chart to indicate that consumers have been thinking about the inconsistent stimulus of a family model Porsche.

Finally, in the pre-regular condition, again, we see some concordance with the pre-perceptions in the other conditions: Mazda and Jeep are similar, as are fast, non-Japanese, and less-variety, and, finally, common shape is grouped with classic. After simply thinking more about Porsches, Benz is grouped with relatively high prices, Mazda and Jeep retain their similarity, and Lexus is grouped with fast and high status. Less-variety and sedan are grouped, as well as the group of non-Japanese and British (presumably in contrast to American and European makes).

The findings on the cliques and equivalence groups were not as simple and clear as we would have liked. However, they demonstrated the richness and variety of the connections that consumers have in their minds when considering and comparing brands. The greater strength of the methods will be illustrated in the discussion that follows regarding the distinct identification of complementary vs. competitive brands. The former are identified via cliques; the latter, via equivalence groupings.

Brands as Complements or Competitors. In this section, we use cliques and equivalence groups primarily to demonstrate the clarity with which they can identify brands that are complements (associated), brands that are competitors (similar), or even brands that are both. We had criticized MDS for not being able logically to distinguish these cases, but cliques and equivalence can do so very easily. However, we recognize that readers may be interested in a broader interpretation beyond our main point, so we described the results for the cliques and equivalence groups in detail in the preceding section. We now turn our focus to the ability of network methods to distinctly identify brands that are associated vs. those that are similar.

Table 13 presents the complementary and substitutable brands. In the economy condition, the cliques of brands indicate those that are complementary and could be co-branded (e.g., cars, parts, or accessories). In the pre-condition, we have {Benz, Jaguar, Mazda}, {Benz, Jeep}, {Benz, Porsche}, {Ferrari, Jaguar}. The equivalence group was {Mazda, Jaguar, Jeep}. Thus, Mazda and Jaguar are both complementary and competitive in perception, but Benz, Porsche, and Ferrari compete with none of the other brands. Following the economy intervention, the complementary sets include {Benz, Ferrari, Jeep}, {Jeep, Mazda}, whereas the competitive sets include {Mazda, Ferrari, Jeep}, {Chrysler, Jaguar}. A Mercedes Benz may elicit associations to Ferrari and Jeep (and vice versa), but a consumer considering the purchase of a Benz is not tempted by any of these cars as alternatives.

Table 13. Complementary (Cliques) and Substitutable (Equivalent) Brands

Economy Porsche		
Pre:	Cliques:	{Benz, Jaguar, Mazda}, {Benz, Jeep}, {Benz, Porsche}, {Ferrari, Jaguar}
	Equivalent:	{Mazda, Jaguar, Jeep}
Post:	Cliques:	{Benz, Ferrari, Jeep}, {Jeep, Mazda}
	Equivalent:	{Mazda, Ferrari, Jeep}, {Chrysler, Jaguar}
Family Porsche		
Pre:	Cliques:	{Jaguar, Mazda}
	Equivalent:	{Jaguar, Benz, Mazda, Jeep}
Post:	Cliques:	na
	Equivalent:	{Corvette, Mazda}, {Chrysler, Jaguar, Ferrari}
Regular Porsche		
Pre:	Cliques:	{Benz, Lexus, Mazda}
	Equivalent:	{Mazda, Jeep}
Post:	Cliques:	{Benz, Porsche, Mazda}, {Benz, Lamborghini}
	Equivalent:	{Mazda, Jeep}

In the family conditions, the complements are {Jaguar, Mazda}, whereas the competitors are {Jaguar, Benz, Mazda, Jeep}. Here is a case where the complements are not distinguishable from the competitors, but the competitors are different from the complements.

Following the family intervention, there were no cliques of complements. As with the centrality findings, dyadic associations have been modified by the family Porsche ad, but large groups, cliques, have not reshaped themselves. The direct competitors are {Corvette, Mazda}, {Chrysler, Jaguar, Ferrari}.

In the control group, the complements started out as {Benz, Lexus, Mazda}, whereas the competitors were {Mazda, Jeep}. After ruminating on Porsche more, the complements were {Benz, Porsche, Mazda}, {Benz, Lamborghini}, and the competitors were {Mazda, Jeep}. Given that this group is analogous to a control group, the structures should bear some resemblance pre- to post-; indeed, the cliques share Benz and Mazda, and the competitor cars are identical with Mazda and Jeep.

As noted earlier, for MDS, both complements and competitors would be represented as points close in space. The brand researcher or brand manager would have no diagnostic information to distinguish the underlying cognitive source of the brands being represented closely.

Discussion

Our goal was to demonstrate how consumer brand perceptions might be represented as associative networks, and how those networks might be used to begin to develop a diagnostic profile of brands. We began by discussing the nature of consumer brand associations—responses that are evoked when consumers think about brands. Existing cognitive theories of associative structures were connected to existing literature on structural networks for the purposes of representing consumer brand associations.

MDS and associative networks were compared in a pre- / post-design, during which respondents were exposed to mock advertising literature describing one of three hypothetical brand extensions. The MDS plots were easily interpretable, partly due to the apparent stability of the method, and partly due to the familiarity of the technique. The associative networks draw from individual's free association responses (i.e., listing their own relevant stimulus consideration sets), and from triadic comparisons, which generate multiple attributes that distinguish among the brands. Given the qualitative and idiosyncratic nature of the data collection procedure, it is not surprising that the resulting associative networks were at times fairly complex. Nevertheless, like the MDS results, the centrality indices were stable with some sensible pre- to post- changes. Of greater importance is the ability of networks to distinguish brands that are associated, and therefore candidates for complementary brand action such as co-branding, from brands that are similar, and therefore substitutable competitors in the minds of the consumers. MDS is limited to represent both of these phenomena in only one manner—by locating the associated or similar brands close in space, which does not assist the brand researcher in separating these very different branding effects.

While the associative network methods are inherently more faithful to the cognitive theorizing of memory structure and activation, neither methodology completely dominated the other. Presumably, the brand researcher wishing to be well informed would use both techniques, given the complementary nature of the information they provide.

At the least, we wished to begin to demonstrate the consumer associative networks' utility as an approach to start addressing the many questions that might be asked regarding branding effects. We believe that we have begun to make progress on this venture.

Notes

1. Ultrametric distance representations (e.g., hierarchical clustering trees) are also useful. Given that hierarchies are a form of network, we focus on spatial and network representations.

2. Associations in network representations of mental models can also possess strengths (e.g., for an association based on many experiences or exposures to communications). In a graph, strength is indicated by the thickness of the line, by the number of links between two nodes, or by a numerical indicator near the link. Asymmetrical relations may also be represented if one node evokes another, but the reverse is not true. We are presenting symmetric, binary ties for the purpose of simplicity; however, we note that what we present is easily extended to ties with strength and direction using standard network methods (e.g., Knoke and Kuklinski 1982).

3. The researcher may collect data in any number of ways. For example, the respondent might make a binary judgment ("Is this stimulus associated with this property? Yes or no?") with the expectation that the simplicity of the judgment is likely to yield more error-free data. Alternatively, rating scales or frequencies may be used, which may be maintained in their continuous form, so that subsequent analyses are effectively weighted by strengths of associations, or they may be dichotomized to simplify subsequent analyses.

4. Clearly the researcher interested in strengths of associations would retain the valued entries. We simplified the entries to indicate only the presence or absence of associations for ease of presentation in this paper. All the techniques we present may be pursued on the non-binary matrix elements as well.

5. Note that because **X'X** and **XX'** are derived from **X**, the entire matrix, **A**, will not be of full rank. However, this would be problematic only if we were trying to apply stochastic distributions to the **A** matrix rather than the **X** matrix. In this paper, we focus on description, but should inferential statistical tests be conducted they would be on **X**, not **A**.

6. In network analysis, there is an isomorphism between the matrix and network representations of the same data; that is, the network depicted in Figure 3 is completely equivalent to the matrix depicted in Table 4. Each time there is a value of 1 indicated in the table (between two brands, two dimensions, or a brand and a dimension), a corresponding linkage is made between the two nodes in the network. For instance, in Table 4, a value of 1 is associated with Porsche and Lamborghini (column 1, row 2); in Figure 3, therefore, a connection is drawn between the two nodes Porsche and Lamborghini. If a network is already in place, like the Aaker network in Figure 1, the connections for any one node, say Meals, are indicated in a corresponding matrix, such that values of 1 are indicated for the pairs Meals-Products, Meals-Brands, Meals-Quality, Meals-McDonald's, Meals-Service, and Meals-Value.

7. For a more comprehensive introduction to network methods, see Knoke and Kuklinski (1982) or Scott (1991). For a focus on networks in marketing, see Hopkins, Henderson, and Iacobucci (1995), Iacobucci and Hopkins (1992), or Ward and Reingen (1990).

8. Ironically, shortly after we began our research, Porsche announced plans to develop and market a sports utility vehicle in a co-venture arrangement with Mercedes. This announcement added a dimension of truth to our cover story; we debriefed subjects by providing them with the *Wall Street Journal* article.

9. The post-MDS plots have been rotated via a Procrustes least squares rotation (cf. Cliff 1966; Iacobucci and Ostrom 1996) to maximally coincide with the pre-MDS plots to enhance interpretability.

10. Researchers desiring fewer (or more) exploratory and idiosyncratic results would move this criterion up (or down). We chose to err for idiosyncrasy and richness of results.

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