MARKET ENTRY STRATEGY FORMULATION: A HIERARCHICAL MODELING AND CONSUMER MEASUREMENT APPROACH

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ABSTRACT

New product development requires large amounts of money and time and presents major risks of failure. An effective strategy for market entry can increase the likelihood of success and improve the potential payoff by focusing development efforts on attractive market opportunities. This paper describes a system of models and measurements designed to support the formulation of such a strategy.

A hierarchical approach to defining the competitive structure of a market is proposed based on Tversky's (1972) theory of choice by elimination of aspects. In our model, product attributes, usage situations, or user characteristics can define the competitive structure. Individual probabilities of purchase are estimated by logit procedures, and alternative hierarchies are tested based on their ability to describe choices when consumers are forced to switch from their favorite product. Statistical tests are developed and choices in a laboratory shopping environment are utilized in a convergent analysis to select the best hierarchical description of the competitive structure.

Opportunities for new product entry depend on the vulnerability of each section of the competitive structure and on the economics of introducing a new product in each. Competitive vulnerability is assessed with perceptual maps, and an order of entry model estimated based on 42 new consumer products is used to reduce the sales potential of later entrants. Profit potential is calculated and a tradeoff of risk, return, and investment is conducted to support formulation of an entry strategy.

In an application to the coffee market a statistically significant and managerially relevant competitive structure is identified. Implications for new product development and research needs are discussed.

INTRODUCTION

In many companies new product development is an important activity in generating growth in sales and profits. Despite the development of management science methods to improve forecasting, the risks remain high (see Urban and Hauser, 1980, for a review of the state of the art). Recently, A. C. Nielsen (1979) reported that of a sample of 228 frequently purchased consumer products which were test marketed in 1977, 64.5 percent were not launched nationally. Since a test market may cost over one million dollars, these losses are substantial to the innovating firms. Losses also occur earlier in the process due to failures in R & D and consumer tests, but the most noticeable, embarrassing, and costly failures are those that occur after a national launch. For example, Polaroid probably lost over 150 million dollars on Polavision instant movies.

The costs and risks of new product development can be considered within the sequential decision process shown at the top of Table 1. The first phase is opportunity identification. This activity includes the selection of a market and the generation of ideas for possible new products. The second phase is design and consists of applied research and the specification of the physical characteristics of the product along with its psychological positioning of benefits to a designated target group. Testing is the third phase and it includes product and advertising evaluation, pre-test market laboratory simulation of consumer response, and test marketing. After all these steps are successfully completed, the product is launched. Table 1 shows the average costs and time for an industrial and a consumer product to go through each step in the process. The times, costs, and probabilities for industrial products are adapted from Mansfield's studies of new chemical, machinery, and electronics products (Mansfield et. al, 1971, Mansfield and Wagner, 1975, Mansfield and Rapoport, 1975). The data for consumer products are judgements based on the authors' experience with over 150 new products, most of which were packaged goods. The variances on these estimates are very large and depend on specific product and company characteristics so the data must be interpreted cautiously.

The average cost to reach the national launch phase for a product successful in each phase is about one million dollars for an industrial product and 1.3 million dollars for a consumer product. But each phase will not be successfully completed for each new product project. The probabilities for successful completion to the launch phase are about .37 (.57 x .65) for an industrial product and .23 (.5 x .45) for a consumer product. This means each phase will be done more than once, on average, before a successful product is developed. The expected cost is the fixed cost of opportunity identification plus the expected costs of each phase. The expected cost of a phase is the cost of the phase divided by the product of the probabilities of completing the remaining steps in the process. Similarly, the expected time is the time for opportunity identification plus the expected time for each phase. This is the time for the phase divided by the product of the probabilities. These calculations indicate about 3 to 3.8 million dollars should be budgeted for development of a successful product. The expected time to develop a product is about 5 years for a consumer product and 10 years for an industrial product. For development and launch, 4.6 and 9.6 million dollars for an industrial and consumer product, respectively, should be budgeted, on average, for a typical successful entry into market.

As indicated in note three of Table 1 the costs and time for a consumer product can be reduced to 2.7 million dollars and 4.6 years by use of pre-test

Table 1

Costs and Risks of New Product Development

(adapted from Urban and Hauser, 1980)

PHASES IN DEVELOPMENT PROCESS

	Opportunity Identification	Design	Testing	Subtotal to Launch Decision	Introduction	TOTAL
Cost ($000's)						
Industrial[1]	50	620	290	960	1,270	2,230
Consumer	100	200	1,000	1,300	5,000	6,300
Time (mos.)						
Industrial[2]	5	27	9	36	15*	51
Consumer	5	6	12	23	4*	27
Probability						
Industrial	#	.57	.65	--	.74	--
Consumer[3]	#	.50	.45	--	.85	--
Expected Cost ($000's)						
Industrial	50	2,261	603	2,914	1.716	4,630
Consumer[3]	100	1,046	2,614	3,760	5,882	9,642
Expected Time (mos.)						
Industrial	5	98	18	121	20	141
Consumer[3]	5	31	24	60	5	65

NOTES: * Includes time from completion of testing phase to the beginning of launch.

Opportunity identification is an activity assumed to produce at least one market worthy of design effort.

1 These figures are adapted from Mansfield and Rapoport (1975, p. 1382-1383) by allocating 50,000 from his applied research classification to opportunity identification and grouping the remaining to applied research and specification under design. Prototype plant is termed testing here.

2 These times are adapted from Mansfield et. al (1971, p. 120) by allocating the total of 51 months to phases assuming no overlap in the launch, manufacturing tool up, or prototype phases. The applied research and specification times were derived by allocating the remaining time proportionally to the percentage of time in these phases.

3 Does not include consideration of pre-test market analysis. Based on a pre-test procedure costing $50,000 with a .6 success probability and a subsequent .8 test market success rate, the expected cost is $2,672 (100 + (200/(.5 x .6 x .8 x .85)) + (50/.6 x .8 x .85)) + 1,000/(.8 x .85)). This is over a one million dollar saving. The expected time is 55 months assuming the pre-test analysis takes 3 months.

market models, but in any case the costs and time requirements are large and emphasize that the new product process should be carefully managed. Quantitative and qualitative methods should be used to improve the probabilities and rewards of success at the design and testing phases. Careful attention should also be focussed on the identification of opportunities before a firm commits approximately three million dollars and five years to develop a product. The opportunity identification phase should include the consideration of alternative markets, assigning priorities to these markets, and consideration of the competitive structure and new product opportunities in the selected markets. Careful development of a market entry strategy can reduce failures in the development process and improve the profits from successful products by targeting development activity to attractive markets that show vulnerabilities to new product innovation and potential to generate a high return on investment.

In some firms, entry is based on technological innovation. Although success can be obtained with this approach, recent studies indicate that 60 to 80 percent of technological innovations are the result of perceptions of market needs and demands (Utterback, 1974, Von Hippel, 1978). This suggests that it is appropriate for an entry strategy to give heavy emphasis to market characteristics and then to target technological innovation at filling these needs.

The purpose of this paper is to develop a market model and measurement system to support the formulation of an effective entry strategy. We assume that a large number of markets have been screened to identify the two or three that most closely match the company's unique capabilities, have desireable market characteristics, and have financial potential (see Urban and Hauser, 1980, for a detailed description of a "market profile analysis" to consider the factors in screening markets). In each of these two or three markets a model-based study of the competitive structure and entry potential would be conducted.

Some of the basic questions to be addressed in this paper are: What products compete with each other in the market? On what basis do they compete? Is there an opening for a new product entry? Are the incremental profits that may be earned worth the risks and costs of development and entry? We will develop a model of the structure for hierarchical competition in a market and a model to estimate potential payoff of a new entry in this market. If the market is permeable to entry and a financial payoff is likely, the resources would be committed to develop a successful new product entry.

This paper begins with a review of existing approaches to hierarchically defining a competitive structure. Building on the positive features of these approaches, a new model is formulated and its hierarchical specification, measurement, estimation, and testing procedures are described. Then, a model of profit potential based on modeling competitive vulnerabilities and the effects of the order of entry of a new product is specified. Risk/return/investment tradeoffs are considered and the entry strategy implications of the models are discussed. An application of the models to the coffee market (four billion dollars in annual sales) is reported, and the paper closes with a consideration of future research needs.

HIERARCHICAL MODELS OF COMPETITIVE STRUCTURE

Many approaches have been used to define a market and the competitive relationship between products within it. The most common is based on similarities of materials or production. For example, the market may be defined as aluminum gears or diesel autos. In many cases, the standard industrial codes (SIC) are used to identify markets.

These are insufficient for new product analysis since they do not reflect the market response which is critical to the success of an innovation. For example, a new plastic gear may compete with aluminum and steel gears for many uses. A VW Rabbit diesel may not compete with a Mercedes Benz 300D although they both have diesel engines. While consumers may see the Mercedes as a part of the luxury car market in which Cadillac, Lincoln, Chrysler, Oldsmobile, Buick, and Jaguars compete, the VW may be viewed as an economy car competing with Datsun, Toyota, Chevette, and Fiesta.

Consider further the structure of the luxury auto market. Figure 1 shows two hypothetical competitive structures for this market. We shall call such structures "trees" and indicate that "branches" divide the products in the market into subsets. In the first tree, the market is grouped by size of car and then by brands, while in the second, the primary grouping is by U.S. or foreign. The strategic implications are very different. Consider G.M.'s situation. If the first structure is correct, it has covered all major sections of the market and has positioned Seville to compete with Mercedes Benz. However, if the second tree is true, G.M. is largely competing with other domestic manufacturers and its own brands compete heavily among themselves. In this second case, the Seville is not competing with Mercedes Benz, and G.M. could consider importing a foreign car to sell in competition with Mercedes or developing a car that would be perceived as "foreign." The second structure would imply a new entry in the foreign luxury market would have a small negative effect on the existing G. M. business and be a possible strategy for increasing sales.

This example emphasizes the need to understand the true competitive structure before committing to new product development. This paper will propose a market-based method for deriving a hierarchical description of the competitive relations between products to support the formulation of a market entry strategy.

Alternative Approaches

Market-based methods of defining competitive structure draw on the fields of economics, psychology, choice theory, and marketing. We briefly review several approaches and indicate each ones strengths and weaknesses. Then we propose a method which builds upon these strengths and attempts to overcome their weaknesses. This review is organized around the criteria used to model competition between products.

Purchase Behavior: The most direct measure of competition is the change in sales of one product due to a change in sales of another ($\partial q_i/\partial q_j$, where q_i is sales of product i). Economists operationalize this notion by the cross price elasticity:

$$\frac{dq_i}{q_i} / \frac{dp_k}{p_k}$$

where q_i = sales of product i

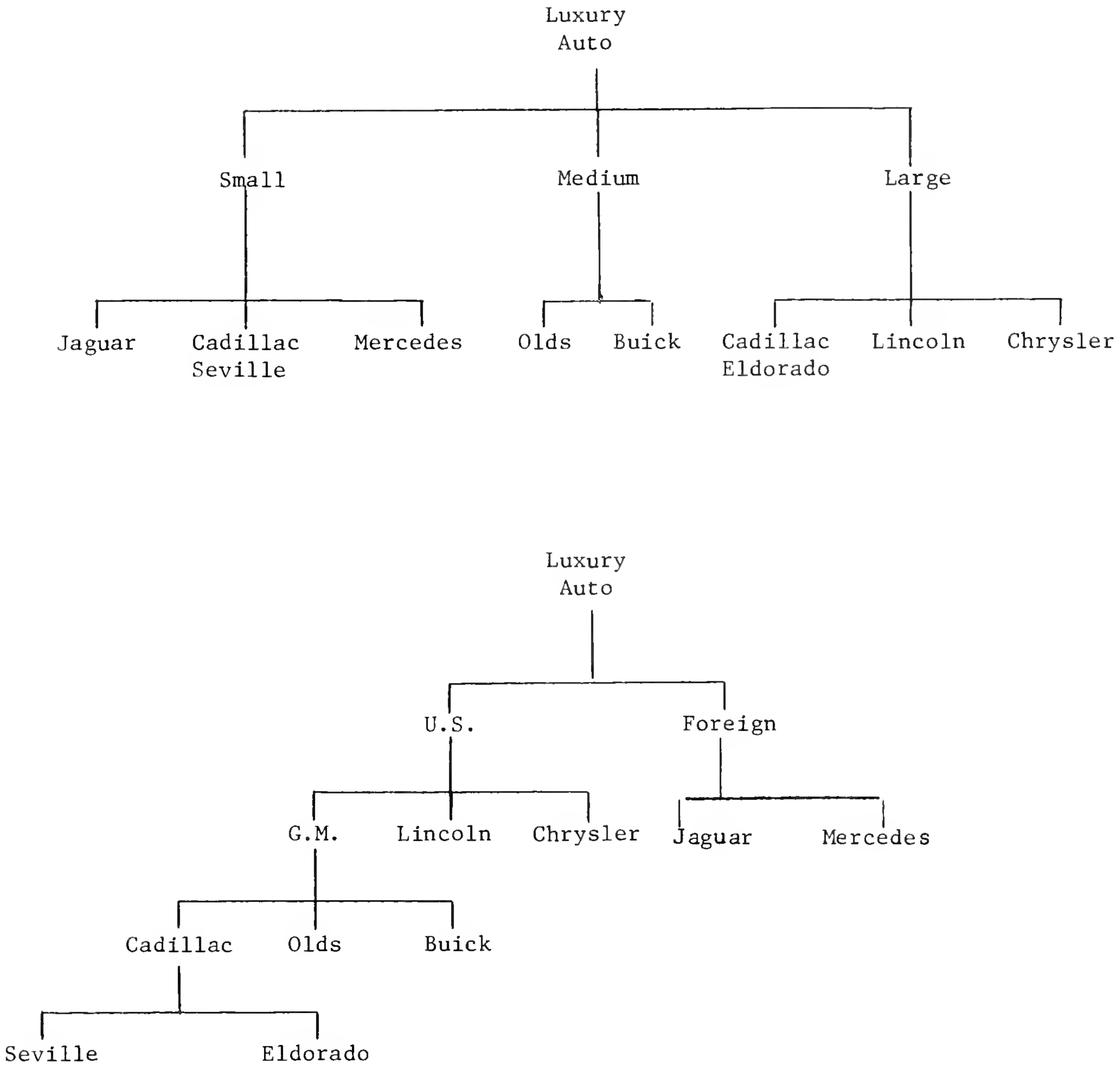
p_k = price of product k.

If it is positive, the products are substitutes and if negative, complements.

Figure 1

Hypothetical Competitive Structures

for the Luxury Auto Market*



* For illustrative purposes, this example only includes some of the over 30 models that might compete in this market.

The notion that the higher the cross elasticity, the more competitive two products are, could be used to describe competitive relationships. It is attractive since it is based on actual sales changes, but presents practical difficulties. The econometric estimation of cross elasticities is difficult for a market of many brands since many cross elasticities must be estimated and these are second order effects relative to direct price and advertising elasticities. New advances in measurement due to electronic retail checkout data and uniform product codes (UPC) may make estimation more feasible in the future for consumer products. Even if the elasticities are estimated, a method to process a matrix of cross elasticities (e.g. 20 x 20) to succinctly define the structure of competition has not been proposed. This is further complicated when one considers cross elasticities due to advertising or promotion are also possible measures of substitution and complementarity (Urban, 1969).

In frequently purchased goods markets, it is feasible to observe sequences of consumer buying based on consumer diaries of purchases. Estimated probabilities of repeat purchasing and switching brands can be derived. Pairs of brands which experience high switching may be considered in competition. Clustering of the observed switching matrix to specify groups of brands which compete has been proposed (Rao and Sabavala, 1978, Kalwani, 1979). Hierarchical clusters could be derived, but in practice the matrix is not very large and many cells may be estimated by small samples. Some of the clusters may be difficult to interpret since all products may not share an observed attribute that can be used to identify it for strategic purposes (e.g., all toothpastes in a cluster may not be anti-cavity brands).

A more theoretical approach to defining a hierarchical competitive structure based on switching has been proposed by Butler (1976). In this approach the criterion is that brands are in competition if switching is proportional to the product of their shares. The method entails testing alternative hierarchical descriptions and selecting the one that best fits the criterion (Morrison and Kalwani, 1977, Rubinson and Bass, 1978). Empirically observed switching can be used if the market is in equilibrium or if it is not, Butler proposes switching rates be derived by maximizing the entropy of the system subject to constraints on market share.

This is an interesting method, but it, as well as other methods based on brand switching, is subject to measurement and estimation limitations. The measures of switching from diaries of consumer purchases reflect household purchases. Individual preferences and usage associations are lost. For example, if the household switches at every purchase opportunity between Crest toothpaste and Colgate, brand switching approaches would find a competitive condition between the brands. But this will not be true if the children are perfectly loyal to Crest and the adults are perfectly loyal to Colgate.

Another difficulty with the method is that the assumed equilibrium condition may not occur often in frequently purchased brands where over 50 percent of the volume is sold on special promotions. In these cases the maximum entropy procedure can be invoked, but one study based on simulations from known structures indicated this procedure was not effective in identifying the hierarchical structure (Rao and Sabavala, 1979).

A final weakness is the lack of statistics to test if one hierarchical structure is significantly better than another. It is not difficult to find a hierarchy that adequately fits a set of data, but in practice other hierarchies also display this adequacy of fit. There is a need for statistical tests to discriminate between alternative competitive structures.

Choice Processes:

One approach to overcoming some of the measurement and estimation problems in methods based on observed sales is to develop models of the individual choice process. Early research led to non-hierarchical models, but recent work has led to models that explicitly consider the hierarchical relationship between products.

Luce (1959) has proposed a choice model that states that the probability of purchase of an alternative is determined by its preference relative to the sum of preferences of all alternatives. This model assumes the relative probabilities of choice between pairs of alternatives do not vary with the size of the set of alternatives offered. This is called the assumption of independence of irrelevant alternatives. This assumption is violated when an alternative competes more with some alternatives than others. For example, Debreu (1960) posed a counter example in the choices between three records: a suite by Debussy (D) and two different recordings of the same Beethoven Symphony (B',B"). If all are equally preferred, Luce's model would imply a probability of choice of 1/3 for each. However, if the two Beethoven records compete with themselves and if the first selection is between either a Beethoven or a Debussy record, the probabilities would be $P(D) = \frac{1}{2}$, $P(B') = \frac{1}{4}$, and $P(B'') = \frac{1}{4}$. This second condition violates Luce's model and the assumption of the independence of irrelevant alternatives. The violation shown by this example could be rectified by a model based on a hierarchical choice process of first Beethoven versus Debussy, and then the choice between the two Beethoven records when Beethoven is selected over Debussy.

Tversky (1972, 1979) has developed a theory called "elimination by aspects" which models choice as a hierarchical process in which all stimuli with a given aspect are eliminated and then choices are made among the remaining alternatives. In an experimental setting in which respondents made repetitive choices from pairs and triples of stimuli (i.e., college applicant profiles on intelligence and motivation) maximum likelihood procedures were used to estimate an elimination by aspects model. The elimination by aspects model could be rejected for only 2 of 24 respondents at the 10 percent level. This notion of elimination by aspects also has received research support from psychologists (e.g., Wickens, 1971).

McFadden (1980) has recently conceptualized the elimination by aspects theory within a framework of generalized extreme value models. His tree extreme values model is a nested sequence of multinomial logit models. A hierarchical structure is posited and probabilities are estimated iteratively by applying the multinomial logit estimation procedures within branches. In an application of these models to transportation mode choice data from San Francisco, he found his tree extreme value model and Tversky's elimination by aspects, produced similar estimates of individual probabilities. Alternative orderings in the hierarchical models did not exhibit significantly better fits (log likelihoods) or lower standard errors than non-hierarchical multinomial logit, but a specific parameter to reflect the hierarchical specification was significantly different from zero. This supports the theory of hierarchical choice. The application also demonstrated the difficulty of discriminating between alternative trees. The significance levels were similar for trees with very different hierarchical orderings and, consequently, very different implications of competitive structure.

The theoretical foundations of hierarchical choice models make them attractive approaches. In addition, McFadden's model is feasible to apply based on observed last choices and measured attributes. Algorithms now are being developed to obtain computational efficiency.

Information Processing: Although a hierarchical model may fit choice data, the hierarchy need not necessarily represent the sequence of decisions individual consumers make. The fact that several trees may fit the data emphasizes this. One should also recall that McFadden's choice model is an aggregate model. It may not represent how individuals behave unless all respondents are homogeneous. An idiosyncratic approach to describing the hierarchical decision process can be made by considering information processing (Bettman, 1979).

Applications have been reported in marketing (Bettman, 1979, Haines, 1971) based on developing a protocol from consumers' statements about what they are considering as they go through a shopping experience. A lexicographic model then is developed to describe their order of consideration of product and use attributes.

Payne (1976) used such a protocol procedure to study choices of apartments, but supplemented it by an information seeking measure. The respondent was asked to choose from a set of apartment alternatives. A matrix of information was presented, each row an apartment, and each column an attribute. Each cell contained a blank card and if a card was turned over, an attribute of an apartment was revealed (e.g., rent or number of rooms). The number of apartment alternatives and the number of attributes was varied across respondents. Payne found that as the number of alternatives and attributes increased, the proportion of cards overturned decreased. For two alternatives, the same number of cards were overturned for both choices, but for larger numbers of alternatives, some alternatives were searched more than others and the chosen alternative was searched most thoroughly. This supports the notion of a lexicographic choice process for complex problems and a trade-off process for simple choice tasks.

Information processing represents the most behaviorally detailed approach to developing a hierarchical model, but it is subject to limitations due to the cost of collecting the information which limits sample sizes and the difficulty of aggregating the findings into a description of a market which is useful to managers (Bettman, 1974).

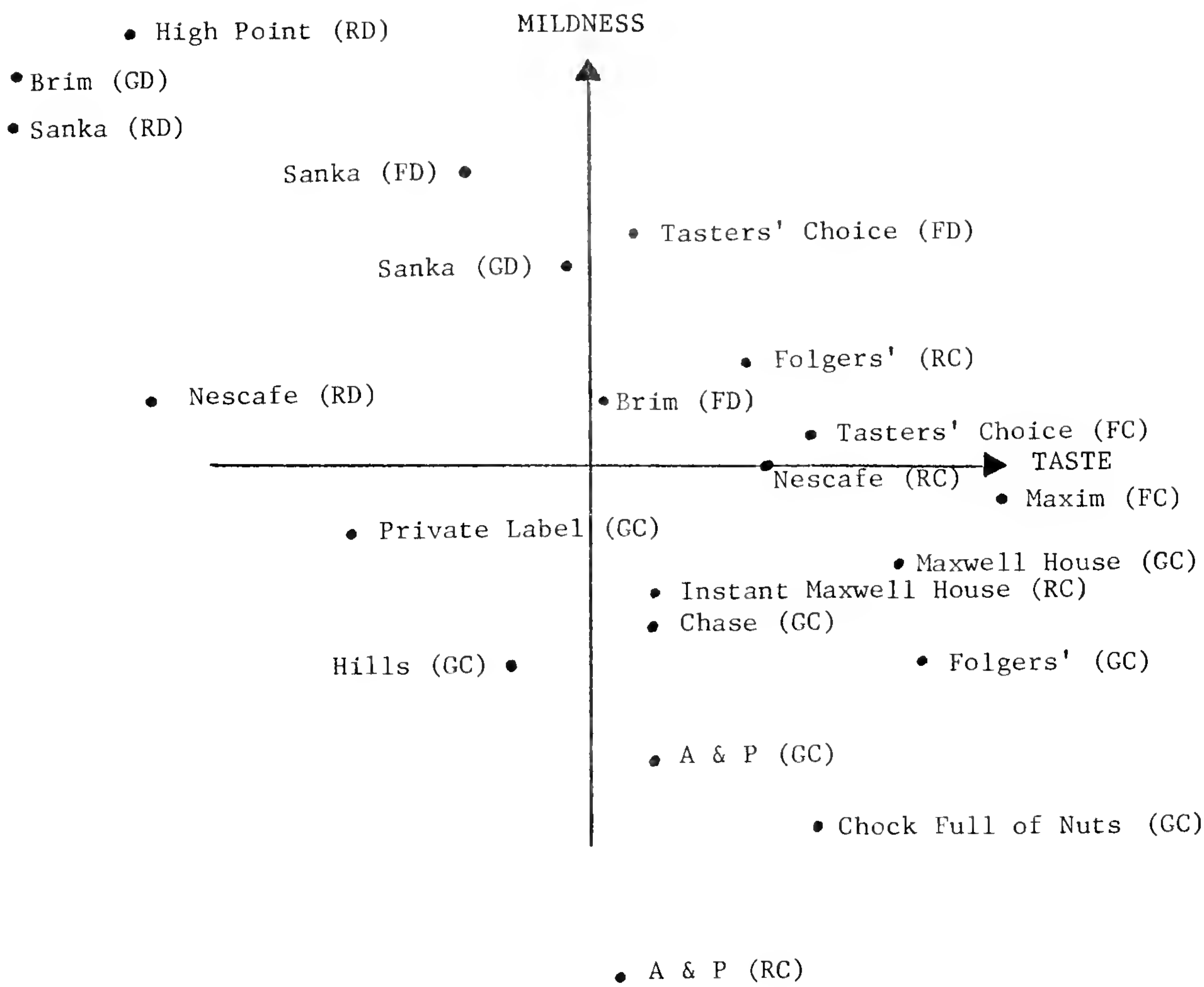
Use Substitution: Examining protocols often indicates the importance of the specifics of the use situation for a product. Situational effects are important in understanding choice behavior (Belk, 1975). Stefflre (1972) has proposed in-use substitution as a measure of competition. If two products are substituted for the same use, they may be viewed as rivals. Stefflre studied 52 prescription drugs by having doctors judge their appropriateness to 52 patient symptoms. A multidimensional scaling of the data indicated groups of products that were deemed to be appropriate to groups of symptoms. Day, Shocker and Srivastava, (1979) applied a similar approach based on a factor analysis of judgements of the appropriateness of brands of products that could serve as a breath freshener under specific use situations.

These approaches emphasize the importance of a situation specific measures in defining a competitive structure, but they restrict their attention only to use similarity and do not reflect purchase behavior or hierarchical choice processes in their definition of competition.

Perceptions: One method of analyzing the appropriateness of products to specific uses is to develop a matrix of similarity between the products (e.g. Z_{ij} = number of situations in which products i and j are appropriate for the same uses divided by the number of uses). A perceptual map can be derived from such a matrix by the application of non-metric multidimensional scaling procedures (e.g., Bourgeois, Haines, and Sommers, 1979).

Figure 2

Perceptual Map of Coffee Market



NOTE:

GC = ground caffeinated

GD = ground decaffeinated

RC = regular caffeinated instant

RD = regular decaffeinated instant

FC = freeze-dried caffeinated instant

FD = freeze-dried decaffeinated instant

Products that are close together could be viewed as more competitive than those farther apart. Products on such perceptual maps can be clustered to define groups of competitive brands or recent hierarchical multidimensional procedures (Carroll, 1976) can be used directly to estimate a competitive structure.

Perceptual mapping methods have been widely used in marketing (Green and Rao, 1972, Stefflre, 1972, Urban, 1975) based on similarity judgements or ratings of products on attributes. In some applications it is assumed the market share of a new product will come from brands inversely proportional to the distance between the new brand and old brands (Urban, 1975). The notion of rivalry between products being represented by the distance between them was proposed initially in economics by Hotelling (1929). His linear model has been extended recently to the multidimensional attribute cases (Lancaster, 1971, and Schmalensee, 1977).

Perceptual similarity is an attractive criterion for defining competition, but it is an intermediary measure of substitution and may not be as valid as actual purchasing. Perceptual maps are commonly used to model choice as a compensatory process by defining directions of increasing utility or maximum utility points (called "ideal" points--Carroll, 1972). The research on information processing and the experiments by Payne cited earlier cast doubt on such a structure in situations with a high number of stimuli. For example, consider the map of the coffee markets shown in Figure 2. This map is based on a factor analysis of ratings of products on 12 attitude scales obtained from interviews of coffee drinkers. (See measurement and application section for description of data collection procedures.) Two dimensions explained 84.3 percent of the variation in the data. Dimension one was most correlated (factor loadings greater than .7) to "taste" scales (fresh tasting, full bodied flavor, rich, right strength of flavor, ground aroma, stimulating, overall taste), and dimension two correlated (loadings greater than .7) to "mildness" scales (does not upset stomach, not bitter). The factor scores for each product are shown in the figure. Note the large number of brands and the lack of obvious clusters of brands that could represent distinct competitive sets. In the authors' experience, these results are typical for a category of many brands. Although perceptual mapping is attractive, it is not the best method for representing competition at the overall level. As Payne's work suggests, it may be an effective method to represent tradeoffs when a lexicographic elimination procedure has preceded it and a simple choice task remains.

Summary and Proposed Approach: Many attractive features are represented in the existing approaches and it is not possible to select one method as best in all situations. If the problem is how to allocate promotional funds across an existing product line, it suggests the appropriateness of research to develop procedures to estimate cross elasticities based on electronic checkout (UPC) data. If the problem is one of identifying and modeling behavioral phenomena, information processing appears attractive. For the problem of market entry, a criterion reflecting switching is useful since the new product must cause people to switch from their existing first choice.

This paper will develop an approach based on Tversky's (1972) theory of elimination by aspects. In an effort to obtain power in discriminating between trees, aggregate switching probabilities will be calculated to represent the situation when the first preference product is unavailable to a consumer. This forced switching scenario will represent the basis for differentiating between hierarchical representations of competitive structures. Specific statistics will be developed to test significance within and between trees. Survey measures of preference and choice will be taken for specific usage situations so the hierarchy can reflect situation specific groups of products that may compete for separate uses. A convergent validation procedure is facilitated by another measure of forced switching based on observation of purchasing in a store when the respondent's first choice is "out of stock." This model is hierarchical, but at the lowest level of the tree where the choice task is simpler, perceptual maps will be added to represent attribute tradeoffs and positioning opportunities.

Model Formulation

In this section we define the competitive structure model called PRODEGY (PRODuct stratEGY) and its associated measurement, estimation, and testing procedures. Later in the paper, market entry analysis procedures based on this model and an application of the model to the coffee market are reported.

Criteria for Hierarchical Specification: Our criterion to judge the appropriateness of a hierarchical tree structure is based on the probability of an individual buying a product in the branch that contains that individual's first preference product under the condition that the first preference product is not available. We aggregate these probabilities across individuals to obtain an average probability for each branch.

$$P_b = \sum_{i \in I_b} P_{ib}/N_b \tag{1}$$

$$P_{ib} = \sum_{\substack{j \in C_i \\ j \in B_b \\ j \neq J_i^*}} \tilde{P}_{ij} \tag{1a}$$

$$\tilde{P}_{ij} = P_{ij}/(1-P_{ij}^*) \tag{1b}$$

P_b = for individuals who have their first preference in branch b, the probability of buying a product in branch b when their first preference brand is unavailable.

P_{ib} = for individual i who has his or her first preference in branch b, probability of buying a product in branch b when his or her first preference brand is unavailable.

P_{ij} = probability of individual i buying product j.

P_{ij}^* = probability of individual i buying the first preference product

$\tilde{P}_{ij}$ = conditional probability of individual i buying product j when the first preference is not purchased (unavailable).

I_b = set of individuals whose first preference product is assigned to branch b

B_b = set of products contained in branch b

C_i = set of products individual i would consider buying

J_i^* = individual i's first preference product

Equation 1b defines the conditional probability of buying a product (j) given the first preference product is not purchased. The unconditional probability (P_{ij}) is the product of the probability of buying product j given the first preference product (j*) is not purchased ($\tilde{P}_{ij}$) times the probability of not buying the most preferred product ($1-P_{ij}*$) and therefore $\tilde{P}_{ij} = P_{ij}/(1-P_{ij}*)$

Equation 1a calculates an individual's probability of buying in the branch which contains his or her most preferred product under the condition that the first preference product is unavailable; it sums the probabilities over the products in that branch which the individual would consider. Table 2 gives an example of these calculations to make the implications of the equations more clear. Individual one considers five products (j = 1 to 5) and the most preferred product is product one (P_{ij} is greatest for j=1); it is a type A product. For illustrative purposes, P_{ib} is calculated for a two-way branching of products with attribute A versus those with AA. The value of P_{ib} = .67 probability of buying a product of type A if product one were unavailable. Similarly P_{ib} is calculated for individual two, but here the most preferred product is of type AA, so individual two's probability of buying is calculated by equation 1a over products of type AA.

Equation 1 averages the probabilities for individuals whose first preference product is in a given branch (e.g. A or AA in Table 2). In the

Table 2

Examples of Calculation of P_{ib}

Products (j)	Product Type	Individuals (i) 1	2
1	A	$P_{11} = .7$	X
2	AA	$P_{12} = .08$	$P_{22} = .45$
3	A	$P_{13} = .15$	X
4	A	$P_{14} = .05$	$P_{24} = .1$
5	AA	$P_{15} = .02$	$P_{25} = .35$
6	AA	X	$P_{26} = .1$
P_{ib}		.67 for $b \Rightarrow A$ $\left(\frac{.15}{(1-.7)} + \frac{.05}{(1-.7)}\right)$	.81 for $b \Rightarrow AA$ $\left(\frac{.35}{(1-.45)} + \frac{.1}{(1-.45)}\right)$

X = not in individual's consideration set two cases in Table 2 the probabilities (P_{ib}) are high. If this were true for all individuals, it would suggest high values of P_b and that branching of attribute A versus AA is a good candidate for the hierarchy.

To obtain an overall measure, the probability of buying in branch b when the first preference products are not available (P_b) is averaged across branches to produce an aggregate tree probability of buying in the branch when first preference is not available:

(2) $$\bar{P} = \sum_b N_b P_b \;/\; \sum_b N_b$$

A good tree structure will have a high value of $\bar{P}$. We seek to find the tree with the highest $\bar{P}$ and assure ourselves that it is significantly better than a random market classification and other possible hierarchical descriptions.

The branching probability in Equation 1 is a function of the assignment of products to branches (P_b), products individuals consider (C_i), and choice probabilities (P_{ij}). To test the significance of a tree we compare P_b for a specific tree to a random assignment of products given no information on consideration sets and choice probabilities. In this case, products would be randomly assigned in equal numbers across the branches and the conditional choice probability calculated. For example, for a two-branch tree, each branch would contain one-half of the brands. Randomly taking away one product from some one arbitrarily designated branch represents the condition of the most preferred product being unavailable. The number of products in this designated branch is (n/2)-1 and (n/2) products are in the other. Given that all products are considered and preferences are equal, the branching probability is the number of products in the arbitrarily designated branch divided by the number available for choice (n-1). The random probability (R_b) is calculated by:

(3) $$R_b = R_{\underline{b}} ((H_{\underline{b}}/G_{\underline{b}}) - 1)/(G_{\underline{b}}-1)$$

$R_{\underline{b}}$ = random probability for branch $\underline{b}$ which is subdivided to contain branch b at next level below it. ($\underline{b}$=0 at top of tree and R_o = 1.0)

$H_{\underline{b}}$ = number of products contained in branch $\underline{b}$

$G_{\underline{b}}$ = number of subdivisions of branch $\underline{b}$ at the next level below it

For the two branch tree and six products shown in table two, the random probability is .4 [1.0((6/2)-1)/(6-1))]. In most cases the number of products is large and random value would approach $R_{\underline{b}}/G_{\underline{b}}$. If P_b is greater than R_b, this represents better assignment than random and if less than R_b, worse than random assignment. The average random probability ($\bar{R}$) for the tree is:

(4) $$\bar{R} = \sum_b N_b R_b / \sum_b N_b$$

The random probability reflects assignment of the products to branches without regard to attribute commonalities while the tree is an assignment with at least one common attribute. It should be noted that the random probability used to test significance does not depend on the particular set of brands individuals consider buying or existing market shares. For example, if two branches exist, the number of products is large, and the market shares of products in each of the branches for the hypothesized tree are .9 and .1 respectively, the random probability of buying for those individuals assigned to a branch when their first preference is unavailable would be approximately .5 in each branch. This is consistent with the elimination by aspects notion which indicates the selection of a branch reflects a decision between attributes and not specific products. Use of the market shares of evoked brands in the random value would result in building a very high information alternative since the major determinants of share and the model proposed here are the consideration set (C_i) and the individual choices (P_{ij}). The random assignment probability ($\bar{R}$) represents the best null hypothesis to test the significance of the hierarchical market structure model presented in this paper.

$\bar{P}$ can be compared to $\bar{R}$ statistically since its approximate distribution is given by the central limit theorem. In the sample sizes and proportions represented here ($n>300$, $.1<P<.9$), the proportions are normally distributed. If we assume the probabilities (P_{ij}) to be multinomially distributed and that trials are independent, the standard deviation of P_b is

$$\sigma_{P_b} = \sqrt{\sum_{i\varepsilon I_b} P_{ib}(1-P_{ib})/N_b^{\,2}}$$

and the standard deviation of $\bar{P}$ is

$$\sigma_{\bar{P}} = \sqrt{\sum_i P_{ib}(1-P_{ib})/\sum_b N_b^{\,2}}$$

(see Appendix One for proofs). One can also test the significance of given branches against the random assignment probability (P_b versus R_b) if the sample size is not too small and the probabilities are not too skewed (Drake, 1967). These statistical tests give a basis for determining if a given tree is statistically significant relative to a random assignment. Similarly, the difference in the overall probabilities ($\bar{P}$) from two trees can be tested by standard procedures to determine if one proportion is significantly better than the other.

<u>Branching Procedure</u>: The first step in developing a tree structure to describe a market is to designate the possible alternatives. Any attribute can be used to define a branch, but each product must be uniquely assigned to a branch before the tree can be evaluated. An alternative is rejected if in any branch

the probability of buying in the first preference branch (P_b) is not significantly greater than the random probability (R_b) at the ten percent level. A second rejection criterion is used to eliminate trees where the switching from the first preference branch is high relative to the random probability. The probability of switching from the first preference branch (b) to another branch (bb) is:

$$(5) \qquad W_{b,bb} = \sum_{i \varepsilon I_b} \sum_{\substack{j \varepsilon C_i \\ j \neq J_i^* \\ j \varepsilon B_{bb}}} \tilde{P}_{ij} \, / \, N_b$$

$W_{b,bb}$ = probability of switching to branch bb from the first preference branch b.

For a tree to be acceptable, we require that the switching probability ($W_{b,bb}$) not be significantly greater at the 10% level than the random probability of buying in the branch switched into when the first preference is not available (R_{bb}). After the alternatives have been screened for the rejection criteria, the tree with the highest average probability of purchase in the first preference branches ($\bar{P}$) is identified.

The application of the rejection criteria and identification of the best branching is carried out at each level of the tree from the top to the bottom. This procedure insures that the least switching occurs at the top branches of the tree and that switching increases as one divides the market more finely. In the market definition problem considered in this paper, the order of branching is important. The sequential procedure assures that the probability of repeat buying ($\bar{P}$) is highest and that the market division is strongest at the top of the tree.

After the top level is considered, alternates rejected by the criteria discussed above, and the best branching identified, we determine if the best branching is significantly better than its nearest rival at the ten percent level based on the overall probability ($\bar{P}$). If so, the analysis moves to the second level based on branching from this alternative. If the best tree is not significantly better than the next alternative, both alternatives are considered for further branching at the next level. Branching stops when no further divisions will satisfy the two rejection criteria given above, when sample sizes become unacceptably small, or when no more candidate hierarchies are available. This typically allows branching to no more than three levels unless a large sample of consumer surveys is collected (greater than 500). If one tree is not significantly better than others at the ten percent level, the tree with the highest probability ($\bar{P}$) is selected and a sensitivity analysis is performed during the entry strategy analysis to determine the effects of the second best alternative on the recommended strategy.

Branching by Uses: As indicated earlier, the specific uses of products can be important in defining a market since positioning a product for a particular use may be a good entry strategy. In this model, uses can be the basis for defining the structure of competition by formulating a tree in which the branches are defined by specific sets of uses, and products are uniquely assigned to branches. For example, in the home cleaner market, cleaning the kitchen may be one branch and cleaning the bathroom another. This would be a good definition if the probability of buying the products assigned to a branch was high for the set of uses that defined that branch and low for buying products assigned to another branch.

This notion is implemented by calculating the individual probabilities of buying again in the "use branch" (products assigned to a particular use) when the most preferred product in that branch is not available. This is analogous to the probability defined in Equation 1. In this formulation, however, individuals are assigned to a branch for a use if they evoke it.

Probabilities are conditioned on each use evoked. For an individual, the probability of buying again in the branch when the most preferred product for a specific use is removed is determined and then the overall probability of trying again in the branch is calculated. The branching probability for the branch defined by use situation $P_b(U)$ is:

$$(6) \qquad P_b(U) = \sum_{u \in U_b} \sum_{i \in I(u)} \sum_{\substack{j \in C_{iu} \\ j \in B_b \\ j \neq J^{**}_{iu}}} \tilde{P}_{iju} \Big/ \sum_{u \in U_b} N_{bu}$$

where $\tilde{P}_{iju} = \dfrac{P_{iju}}{1-P_{iju}^{**}}$

P_{iju} = probability of individual i buying product j for use u and $\sum_{j \in C_{iu}} P_{iju} = 1.0$

P^{**}_{iju} = probability of individual i buying the most preferred brand of the set of products assigned to the branch b for use u contained in U_b

U_b = set of uses that define branch b

$I(u)$ = set of indivduals who evoke use u

C_{iu} = set of products individual i considers for use u

B_b = set of brands assigned to branch b

J_{iu}^{**} = individual i's most preferred product for use u that is contained in branch b

N_{bu} = number of people in branch b with use u.

Note that the probability is conditioned on the most preferred product in the branch being unavailable rather than the overall first preference. This is because it is not necessary that the respondent's first preference product for a use be one of the products assigned to that usage branch. If it is not, however, the probability ($\tilde{P}_{iju}$) will be low when summed over the products in the branch. If this phenomena is widespread, the overall probability $P_b(U)$ will be low and the tree structure will be rejected as it should be.

The overall probability ($\bar{P}(U)$) can be compared to the random probability ($\bar{R}(U)$) and probabilities ($\bar{P}$) from other trees where branching is not based on use,but on attribute branching. A statistical judgement can be made as to whether use is a significant method of defining the competitive structure and if it is significantly better than other tree structures.

The association of products (B_b) and uses (U_b) in a branch (b) can be made by prior grouping or by a factor analysis of a matrix of the average ratings of appropriateness of each product (j) for each use (u). (See application reported later for empirical example.) The factor loadings will reflect the intercorrelations of the uses and are the basis for grouping uses into larger sets. The factor scores will indicate the position of each product on the use dimension and products can be assigned to use set based on their highest factor score. This provides a set of uses and products for definition of branches for evaluation by Equation 6.

Branching by Users: Similar procedures can be used to group users and assign products to branches to test structures based on users. For example, children and adults are two possible definitions of branches for breakfast cereal.

If products can be uniquely assigned to one group or the other, the probability of buying again in a branch can be calculated. This probability is:

$$(7) \quad P_b(S) = \sum_{i \varepsilon I_b(s)} \sum_{\substack{j \varepsilon C_i \\ j \varepsilon B_b \\ j \neq J_i^{**}}} \tilde{P}_{ij} \,/\, N_b$$

where $\tilde{P}_{ij} = \frac{P_{ij}}{1-P_{ij}^{**}}$

$I_b(s)$ = set of individuals with characteristics (s) that are assigned to branch b

J_i^{**} = individual i's most preferred product of those assigned to branch b

P_{ij}^{**} = probability of individual i buying the most preferred product of those assigned to branch b.

Individuals can be grouped into sets for the definition of branches by a priori designation or cluster analysis of individual characteristics. If clustering is used, those who have similar patterns across products could be grouped together and products would be assigned to the group which has the highest average preference for them. This branching alternative can be evaluated by Equation 7. If the assignment and clustering is good, the branching probability will be high; if not, the probability ($P_b(S)$) will fail the statistical criteria for branching and the user based tree rejected.

In searching for the best hierarchical structure to define a market, alternatives based on product attributes, uses, and users can be compared. The branching procedure across these alternatives will use the probability of buying again in the branch ($P_b(U,S)$ to find the best tree definition at each level. The highest average probability ($\bar{P}(U,S)$, Equation 2) represents the best tree and the statistical significance of differences between alternatives can be calculated.

Heterogeneity: The procedures outlined above assume that consumers have a homogeneous view of the competitive structure of the market. This assumption can be tested by modeling the heterogeneous segments with separate trees and determining if this heterogeneous description is significantly better. First, alternative hierarchical structures (H) are posited and then individual probabilities (P_{ib}, Equation 1a) are calculated for each alternative. The result is a probability for each individual of buying in the branch to which he or she was assigned under each alternative tree ($P_{ib}(H)$). Each individual is assigned to the overall tree hypothesis (H) he or she most strongly supports. This is where his or her probability ($P_{ib}(H)$) is highest.[4] These probabilities are aggregated for the individuals assigned to each tree ($\bar{P}(H)$) and then combined as a weighted average to obtain an overall goodness of fit measure ($\bar{\bar{P}}$). The significance of the gains due to allowing heterogeneity can be tested on an overall basis by a significance test for the differences in proportions ($\bar{P}$ versus $\bar{\bar{P}}$).

If heterogeneity is significant, the heterogeneous description would be subjected to managerial analysis. If heterogeneous groups can be demographically or attitudinally identified, separate products could be targeted to each of them. If not, one product would be developed based on the weighted average response from the heterogeneous description of the competitive structure. Sensitivity analysis would be used to see if the inclusion of heterogeneity changes those market entry strategies.

Measurement, Estimating and Testing

The hierarchical model input requires individuals' evoked uses, the set of products considered and their appropriateness for each use, and the probability of purchases of each product considered. Survey measures and statistical estimation procedures provide these inputs.

Direct survey measures are collected at a central location for a sample ($n \geq 300$) of category users. See Silk and Urban, 1978, for more detailed description of such sampling and measurement methodology. In order to determine the products consumers would consider for specific uses, respondents describe their last and other uses of the product.

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[4] An alternate approach is to cluster individuals based on their patterns of fits ($P_{bi}(H)$). See Brudnick (1979).

An interviewer classifies the specific use situations into one of a set of more general usage classes. Pre-testing and focus group interviews are conducted to assure that all the use situations are identified and classified. For each use the respondent indicates what product she last used, has on hand or would consider using in the situation. (See Appendix Two for an example that shows coffee use situations and the proportion of people who would consider each coffee product for each use.)

Given the consideration set (C_i) and uses (U), the next task is to estimate the probability of purchase (P_{ij}). Several measures may be utilized. The most elementary is to assign a probability of $1/n_i$, where n_i is the number of products in the consideration set C_i, to each product in an individual's consideration set. This makes the restrictive assumption that each product is equally preferred, but if it gives results (P_b,$\bar{P}$) that are not significantly inferior to other methods, considerable measurement costs could be reduced by not collecting preference data. The equal preference assumption can be relaxed by collecting rank order or scaled preferences. If rank order preferences are collected along with the identification of the respondent's last purchase, a probability can be estimated when i is the r^{th} ranked product by:

(8) $$P_{ij} = W_r(j) / \sum_{j \varepsilon C_i} W_r(j)$$

where $W_r(j)$ = percent of respondents who last purchased their r^{th} preferred product and where in a specific case product j is r^{th} ranked

This assumes that preferences are constant (zero order purchasing process) and all individuals have the same probability of buying their r^{th} ranked product.

The most attractive model of probability of purchase is the logit model:

(9) $$P_{ij} = \frac{\exp(\beta \ln A_{ij})}{\sum_{j \epsilon C_i} \exp(\beta \ln A_{ij})}$$

A_{ij} is the measured preference for brand j and individual i

β = parameter

To support this model last purchase and constant sum preference measures (Torgerson, 1958) would be collected. Maximum likelihood procedures are available to estimate the parameter β (McFadden, 1970, McFadden and Wills). and statistical tests of the goodness of fit of the model can be applied (McFadden, 1970, Hauser, 1978).

The logit model allows each individual to have different probabilities of purchase over their consideration set of products, but the model assumes independence of irrelevant alternatives. In each empirical case, tests should be conducted to determine if the assumption is violated. Specific tests can be applied based on the structure of residuals (McFadden, Train and Tye, 1977) or differences in estimates when enlarging the evoked set (Silk and Urban, 1978). If independence of irrelevant alternatives is violated, another problem appears in the calculation of the individual set of probabilities of choice when the first preference is removed ($\tilde{P}_{ij}$) since Equation 1a assumes a proportionate reduction in all other probabilities after removing one product.

If the assumption is violated, one possible recovery procedure is to employ a hierarchical logit model (McFadden, 1980) to estimate the choice probabilities (P_{ij}). Theoretically the hierarchical logit is the best way to estimate the individual probabilities, but the properties of the hierarchical logit in the face of the heterogeneity that is to be encompassed in this model are not well known. In addition, the use of the hierarchical logit becomes rather cumbersome because for each hierarchy tested, the probabilities (P_{ij} and $\tilde{P}_{ij}$)

must be re-estimated by the hierarchical logit procedure. In practice, if the probabilities (P_{ij}) estimated by the multinomial logit (Equation 9) and the hierarchical logit are highly correlated, this cumbersome procedure can be avoided along with the need to assume homogeneity of the hierarchy across individuals. This issue will be considered further in the application section of this paper.

With measures of consideration sets, evoked uses, and estimates of probability of choice based on measured preferences for products for each use and the last produce used, the branching procedures and criteria can be applied.

During the survey of respondents, ratings of products on selected attribute scales and demographic data are collected. The ratings are used to characterize product perceptions (see entry analysis section) and the demographics to identify the composition of branches.

The procedures outlined above derive a hierarchical tree that best fits the measured preferences and choices. In order to gain confidence in this description, an experiment is conducted at the end of the respondent interview. Respondents are given an opportunity to purchase a product in a simulated retail store with coupons given them as compensation for the interview. This procedure has been successfully used to estimate trial of new products (see Silk and Urban, 1978). In this case it is modified by removing each respondent's most preferred product from the shelf in the lab store. This simulates forced switching and the observed proportions who remain in a predicted branch can be calculated. These observed proportions (P_b') can be used analogously to the proportions from the choice model (P_b in Equation 1) to find the best tree. If the best tree in both cases agrees, confidence in that hierarchical structure increases. If the solutions are different, possible biases in data collection or estimation should be examined to see if one solution should be rejected or modified. If both solutions are acceptable, the initial proportions (P_b) are considered as priors and updated by Bayesian procedures (Raiffa and Schlaiffer, 1961) to be:

(10) $$P_b'' = (P_b\, N_b + P_b'\, N_b')/(N_b + N_b')$$

P_b' = proportion who buys product in branch when shopping in environment where most preferred product is removed from shelf

P_b'' = updated probability of buying product in branch when most preferred product is not available

N_b = number of individual observations in branch b in choice model

N_b' = number of individual observations in branch b in shopping environment

This is equivalent to the classical procedure of pooling the data. Based on the updated probabilities (P_b''), the branching procedure is again applied to define the best hierarchical description of the competitive structure.

The outcome of the measurement, estimation and testing is the specification of a hierarchical structure that is statistically significant and supported by convergent estimation from the choice probability model and testing from the observed forced switching measures.

ESTIMATING NEW PRODUCT ENTRY POTENTIAL

After establishing a hierarchical model of the structure of competition, we next must determine if there are opportunities for new product entries. The profit potential of a new entry will depend upon the existence of a vulnerability of existing products to a superior product, growth in the market, costs (production and marketing), and margins. In this section, we discuss these profit factors, risk/return tradeoffs, and entry strategies that can be utilized in response to the identification of an entry opportunity.

Competitive Vulnerability

A number of products will be competing in each of the submarkets defined by the final branches in the tree used to define the structure of competition. In each of these submarkets the relative position of products can be represented by a perceptual map derived from factor analysis of consumers' product attribute ratings (Urban, 1975). Figure 3 shows a perceptual map for regular instant coffees. This is based on the average factor scores of these individuals represented in the overall map in Figure 2 who had a first preference for a regular caffeinated instant coffee. The perceptual maps give the coordinates of each product on the two underlying dimensions. The importance of each of these dimensions can be estimated by correlating the product coordinates with consumer preference in a compensatory model of attribute tradeoffs. A linear form of such a preference model is:

(11) $$A_{ij} = \sum_{d} \alpha_d X_{ijd} + \varepsilon$$

A_{ij} = preference for product j and individual i

α_d = "importance" of dimension d

Figure 3

Perceptual Map of Caffeinated Regular Instant Coffees

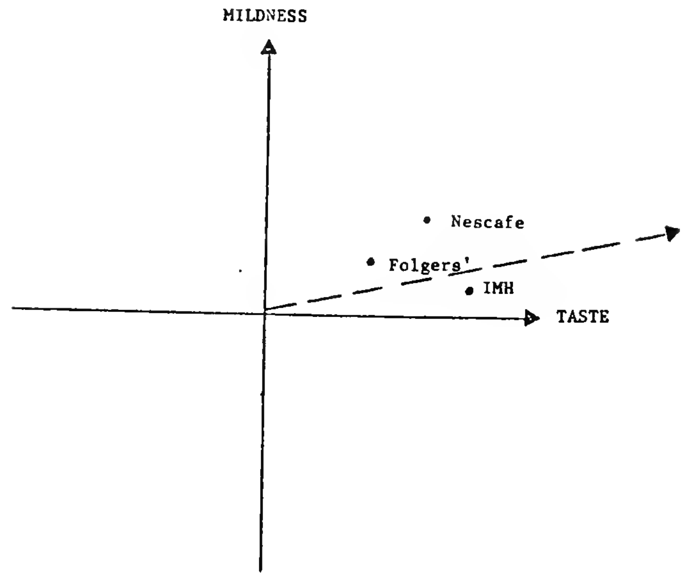
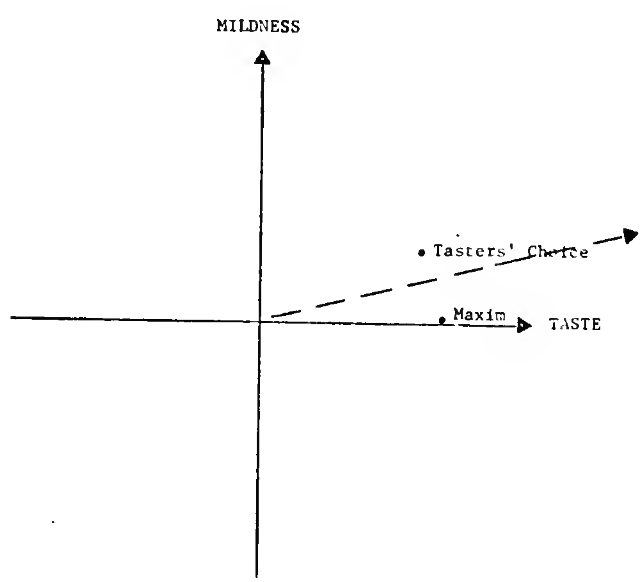


Figure 4

Perceptual Map of Caffeinated Freeze-Dried Instant Coffees



X_{ijd} = attribute score of product j on dimension d by individual i.

ε = error term, $N(0,\sigma^2)$

More elaborate models could be used to represent nonlinearity. (See Hauser and Urban, 1977, for a review.)

This use of a compensatory model of preferences at the bottom of the tree is consistent with Tversky's (1972) and Payne's (1976) findings that lexicographic procedures are used for complex tasks and compensatory procedures for simple tasks. The vector in Figure 3 reflects the relative importance of taste and mildness. The further out the perpendicular projection of each product on this line, the higher the preference. The importances shown in Figure 3 were derived by a regression of observed preferences against the individual factor scores in Equation 11 ($F(2/173)=33$, $R^2=.27$, $t_1=7.3$, $t_2=3.3$).

Nescafe is positioned as being the mildest, but it is not perceived as having as good a taste as Instant Maxwell House. The competition is vulnerable to a new brand that can achieve the mildness of Nescafe and the taste of Instant Maxwell House. Figure 4 shows a map of caffeinated freeze-dried instant coffees, assuming it is in a different product segment. It is similarly derived from Figure 2 for those who have first preference for a freeze-dried, caffeinated instant coffee, and it shows little vulnerability since Taster's Choice is very well positioned on the tradeoff between taste and mildness. In this illustrative example both segments value mildness and taste, but the competitive product sets are different.

If the new product is positioned exactly at the same point as Taster's Choice in Figure 4, it probably would not gain the same share since it would be competing against a long-established brand without offering any apparent advantages. To capture phenomena of positioning and order of entry, we model potential as a function of the magnitude of the positioning opportunity and the number of brands previously entered in the market. The market share potential for the new product is:

(12) $$M' = M^*(S/S^*)E_e$$

where M' = relative share potential for new entrant in branch

E_e = order of entry index

M^* = existing market share for first product in market

S^* = predicted share of purchases for the first product in market among those who would consider; it.

(12a) $$S^* = \sum_{i \varepsilon F} P_{if}/N_F$$

where F = set of individuals who have the first product in market within their consideration set (C_i)

N_F = number of individuals in set F

P_{if} = probability of purchase of first product in market by individual i (Equation 9)

S = predicted share of purchases for those who would consider new product:

(12b) $$S = \sum_i \left[\exp(\beta \ln A_{ik}) / \sum_{j \varepsilon C_i} \exp(\beta \ln A_{ij}) \right] /N$$

where A_{ij} = preference for product j by individual i (Equation 11), j = k for new product

N = number of respondents

β = logit parameter (Equation 9)

The S/S* term is the share of the new product relative to the first product in the market. It reflects the positioning advantage of the new product because the new product share depends upon the preference that positioning earns. This positioning opportunity is usually estimated under the scenario that the new product could combine the maximum levels of the attributes now present in existing products (e.g., in Figure 3 -- the taste of Maxwell House and the mildness of Nescafe). These maximum levels (X_d*) are substituted in Equation 11 to estimate the preference for the new entrant (A_{ik}). In some cases where R & D capabilities and potential are high, preference may be predicted based on greater than the observed best levels (X_d*). In others it may be deemed technically impossible to achieve the best values (X_d*) in both dimensions and, therefore, an intermediate combination would be used to predict preferences. With the first procedure, S/S* is greater than or equal to 1.0. If the fit of the model used to predict preference (Equation 11) is not good, the amount by which S/S* exceeds one will be subject to error. In the case shown in Figure 4, the t's are significant, but the R^2 is not high. Care should be exercised if the decision to enter is sensitive to S/S*. In this case S/S* = 1.01 and low sensitivity is present. The conservative position is to set S/S* = 1.0 and this should be done if the F statistic or coefficents for the preferencc model are not significant. This is equivalent to assuming our position will be equivalent to the first product in the market.

The order of entry index (E_e) reflects the share of the new entrant relative to the first product in the market when they are positioned identically. The index may be expected to decline due to difficulty entrants experience in gaining awareness, evoking, and trial in the face of consumer loyalties and retail distribution inertia built up by the first product in the market. For example, in the coffee market, Sanka was the first decaffeinated coffee and retains a dominant share despite a number of similar subsequent entries. The penalty probably would be greater for the third entry (e = 3) than the second (e = 2), but not twice as great. The exponential form ($\exp^{-\alpha e}$) is an appealing model for this decay since it declines nonlinearly and asymtotically approaches zero.

Although there is a penalty for later entry, it can be offset by a positioning that is superior to the first product (represented by $S/S^* > 1$). For example, Maxim was the first freeze dried instant coffee, but Taster's Choice, although second in the market, achieved a better positioning and a greater market share. The model in Equation 12 allows both positioning and entry effects to operate.

In order to preserve the requirement that shares sum to 1.0, we normalize new product share to get the entry share potential ($\bar{M}$):

(13) $$\bar{M} = M'/(1 + M').$$

Estimating Entry Order Effects

The ratio of shares of the first product and later entrants can be observed ($R = M'/M^*$). If relative positioning effects (S/S^*) also have been measured, the index of entry (E_e in Equation 12) can be estimated empirically. Solving Equation 12 provides a set of observed values of the index (E_e).

(14) $$E_e = (M'/M^*)/(S/S^*)$$

If we assume the decline in the index is exponential we have:

(15) $\hat{E}_e = \exp^{-\alpha(e - 1)}$, where $\hat{E}_e$ is the predicted order of entry index. Alpha (α) can be estimated by a log linear regression of Equation 15.

Data on purchase and preferences for established brands were available from pre-test market analyses conducted in 16 markets of frequently purchased brands (e.g., dandruff shampoos, fabric softeners, light beer, acetominaphen pain relievers, dry bleach, high filtration cigarettes). Market share and perceptual ratings data were available for 42 products (see Silk and

Urban for the measurement procedure used in collecting this data). Alpha was estimated by the regression equation:

$$\ln(R_{ec}/(S_{ec}/S^*_c)) = \alpha(e - 1) + \varepsilon \quad (16)$$

R_{ec} = share of last purchases for entrant e divided by the share of purchases of first product in market in category c.

S^*_c = predicted share of purchases for first product in category c (see Equation 12a)

S_{ec} = predicted share of purchases for product entry e in category c (Equation 12b)

e = e^{th} product to enter category c ($e > 1$).

The results were statistically significant at the ten percent level (t=1.6, 25 degrees of freedom). The estimated α of -.53 implies entry index values of:

$\hat{E}_1 = 1.0$

$\hat{E}_2 = 0.58$

$\hat{E}_3 = 0.34$

$\hat{E}_4 = 0.20$

The input to this estimation was based on relationships at a point in time and does not represent the patterns of share change over time. It assumes that if positioning is equal, the ratio of the share of an entrant relative to the first product is constant as new products enter.

An alternative estimate of α was obtained using a robust method. Since e in Equation 16 takes on discrete values (2, 3, . . .) and since most of the products were drawn from positions 2 and 3, we have distinct groups of values for the dependent variable--one group for position 2 and one group for position 3.[5] Medians were calculated for each group, and α was fit to them. The resulting estimate was -.54--almost duplicating the log regression results.

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[5] Techniques for systematically identifying outliers in the data were explored. The "hat" matrix, a usually helpful instrument in this area, was of no value to this application, since it depends only on the values of the independent variables and its diagonal was constant at each entry position.

The entry index values demonstrate the substantial penalty apparent in these markets for later entry if a parity positioning is used. However, as Equation 12 indicates, this can be overcome with superior positioning. In four of the categories studied, a later entrant achieved greater share than the first product. In all these cases, the positioning (S/S*) was superior to the leader.

To simulate the share potential of a new entry, substitute the appropriate E_e value in Equation 12 and multiply by estimated share of choices for the new product relative to the first entrant (S/S*) and the first entrant's share (M*). The share of choices of the new product is a function of preference for it, which in turn can be estimated from the model that relates perceptions into preference (Equation 11).

Profit Potential and Risk/Return Tradeoff

Given an estimate of the share potential for a new entry (Equations 12 and 13), our next task is to calculate the expected profit and rate of return on investment that would result from a commitment to develop a product entrant for this market. Then a tradeoff between risk and return must be made and an entry strategy designated.

We utilize a simple model to calculate total profit returned over the product's life cycle:

$$(17) \qquad TP = \sum_{t=1}^{L} (M_t W_t (K_t - Z_t) - Y_t) D_t$$

TP = total discounted profit

M_t = market share of new entry in year t (t = 1, 2, . . . L) where L is end of life cycle

W_t = industry sales volume in year t

K_t = price in year t

Z_t = unit cost in year t

Y_t = sustaining advertising, selling, and promotion costs in year t

$D_t = 1/(1 + TR)^t$ = discount factor, where TR = target rate of return on investment

Industry sales are usually subject to a life cycle of birth, growth, maturity, and decline (Polli and Cook, 1969, and Cox, 1967). Life cycle models such as the one developed by Bass (1969) can be used to forecast the sales of a total submarket based on previous history. In very new markets where little previous data exists, judgement is required.

The market share ($\bar{M}$) for the entrant can be estimated as indicated (Equations 12 and 13), but this eventual share must be reflected in the annual share (M_t) growth to its ultimate value ($\bar{M}$). In frequently purchased products, this happens rapidly over the first two years. In other product areas share growth may be expected to be slower.

The costs of achieving the share potential are related to advertising and promotion. In the introductory period costs usually are higher than sustaining levels. The costs corresponding to this share potential achievement could be approximated by the past industry spending rate per share point for introduction marketing expenditure multiplied by the share potential. Analogously the sustaining level is the ultimate share ($\bar{M}$) times the industry spending rate per share at maturity. This assumes the new entrant will experience industry average efficiency in its marketing spending.

Product costs (Z_t) and price (K_t) may be judged to be similar to existing industry norms in calculation of profit. If new innovations are to be made in costs, these can be reflected in the calculation. One phenomenon that may affect the costs is economies of scale in production. In some industries costs decline as production volumes increase (Boston Consulting Group, 1970). These learning phenomena also affect prices since as volumes and costs decrease, competition will lower prices. In markets where such phenomena exist, establishing a substantial share position is important. The share potential ($\bar{M}$) must be high to justify entry and must be heavily funded to retain a significant industry presence. In industries where these phenomena exist, the simple model (Equation 17) must be expanded to consider the simultaneous effects of price on sales, sales on costs, and costs on price (Bass, 1978, Dolan and Jeuland, 1979, and Robinson and Lakhani, 1975). The result in some analyses will be a full venture simulation to reflect these effects and other cost and distribution complexities.

The final adjustment to profit in Equation 17 is to discount (D_t) at the firm's target rate of return. This discounted cash flow can be compared to the required investment to evaluate the desireability of committing to entering this market. The investment is the cost of fixed production facilities and the expected cost of developing and introducing the product. Table 1 provides average expected costs which include the initial marketing expenses and development costs. (Note Equation 17 includes only the sustaining marketing costs (Y_t).) At the time of formulating an entry strategy, the introductory marketing expense should be considered as an investment.

The decision to commit to development should reflect a balancing of risk and return. Several methods exist to make this tradeoff. (Keeney and Raiffa, 1976, Hertz, 1969, and Pessemier, 1977.) The simplest approach is to consider the amount by which expected return exceeds investment and judge whether it is enough of a margin of safety to cover unforeseen events. This approach can be formalized by estimating a distribution around each variable in Equation 17 and calculating the standard deviation of the discounted profit (see Urban, 1968, Beattie, 1969). If the distribution is assumed to be normal or derived by Monte Carlo analysis, the probability that the discounted profit exceeds investment can be calculated. This is equivalent to the probability that the rate of return exceeds the target rate of return. If this probability is above the firm's criteria, entering this market would be recommended.

Entry Strategies

The most obvious strategy is to fill the opportunity described by the hierarchical market definition and entry potential analysis. This is appropriate if the probability of achieving the target return on investment is high. Resources could be devoted to idea generation and design activities to develop a product to fit the vulnerability in the competitive structure. (See Hauser and Simmie, 1979, for a modeling approach.)

This single product strategy may not be appropriate if the firm offers an existing product line. In this case the incremental effect should be considered. The major market branches should be covered by products from the line, but multiple entries should be minimized unless they are clearly differentiated in their positioning within the markets. If duplication exists, resources should be concentrated on one product in each market subsegment. Products could be dropped or repositioned to achieve effective coverage of the market opportunities. The maps and hierarchical tree provide the information needed to assess the duplication and coverage across the market components.

Another possible product line strategy is to deter competition by filling all possible openings even if duplication results. We do not recommend such a strategy because it will produce duplication while risking antitrust actions (Schmalensee, 1977). We recommend innovation rather than deterence as a source of profit and direction for resource allocation, but if deterence is the selected strategy, the maps and branchings can point out gaps to fill in pre-empting competition.

Product line effects may also be present in firms which are entering a market for the first time. If the dimensions are the same in each branch, it may be highly efficient to position a product line because the overall advertising expenditures will payoff in several rather than only one branch. Another justification for a line is if one of the common dimensions is the availability of a full line of products. Then the perception of comprehensiveness that is necessary can be fulfilled by a product line. In these cases, the ROI would be calculated for the line with due regard for demand and cost interdependencies (Urban, 1969).

Another entry strategy is by acquisition. If the maps show a well-positioned brand produced by a regional firm, the acquisition and national marketing may pay off. Similarly, if users see a product with low market share as well positioned, acquisition and application of marketing resources may pay off. The models allow calculation of ROI gains by national positioning and gains due to marketing to achieve better positioning and evoking. Such input is very useful in negotiating an acquisition and determining how much should be paid.

All the above strategies are evolutionary since they work within the current market definition. Another approach is to revolutionize the market by creating new branches or new dimensions. For example, Contac's time release product revolutionized the cold remedy category and home pregnancy kits created a new market segment for health aids. Such a revolutionary approach to creating new markets can be very rewarding, but it is also risky. Polaroid lost millions of dollars on Polavision, trying to revolutionize the home movie market by adding an instant development feature.

We recommend a portfolio approach based on achieving growth and development goals with a combination of some projects based on positioning within the structure and some on changing it. Whether an evolutionary or revolutionary strategy is used, it is wise to understand the existing market structure and competitive dimensions. With an in-depth understanding of the current structure of competition, a revolutionary strategy can more effectively be pursued.

APPLICATION

Problem Setting

We assume we are in the position of a manufacturer of retail food products and that after evaluating many categories, found coffee to be desireable based on a set of overall screening criteria (see Urban and Hauser, 1980). Our question now is: Should we commit to develop a new entrant into the coffee market? If yes, should it be decaffeinated or caffeinated, ground coffee or instant, and if instant, freeze dried or regular instant. We apply our proposed model in this setting to evaluate the structure of competition, the potential for a new product, and entry strategies.

Data Collection

In accordance with measurement procedures outlined above, 295 users of coffee (those who drink more than one cup of coffee/per day at home) were interviewed in Springfield, Mass., and Indianapolis, Indiana in July and August of 1977. Respondents were interviewed after being recruited in a shopping mall and quotas were set to assure at least 50 respondents used each major type of coffee (ground/instant, caffeinated/decaffeinated, freeze dried). It should be pointed out that this survey data was not used to estimate market shares -- they were based on warehouse withdrawals. For each respondent uses were evoked, the products considered for each use, and the last product used were identified (see measurement section of this paper and Appendix Two). Preferences for products for each use were obtained on a seven point scale (extremely well liked to very much disliked). Brands were rated on 12 product attribute scales (see discussion of Figure 2 for identification of scales). After providing demographic data and answering questions on coffee consumption, respondents were given an opportunity to purchase coffee for their most frequent use with a two dollar coupon they were given as compensation for participating in the interview. When the respondents reached the shelf, they found their first preference product "out of stock." Eighty-five percent of the people made a purchase in the lab and seventy percent noticed their favored brand was missing. At the close of the lab phase, respondents were requested to participate in a usage panel in which they would record for a week each cup of coffee served at home in a diary (when, kind, brand, who present, how many cups, who prepared). Sixty percent returned a complete diary. Two weeks after the lab, respondents were called back to determine their home inventory of coffee (kinds, brand, open or not, size of package). The panel and pantry check were conducted in this application to provide additional insight into the effects of the use situation on product choice. In most applications, the evoking and preference by use would be sufficient to determine if use is the best basis of a hierarchical branching in a market.

Estimation of Probabilities of Choice

Based on these data, individual probabilities (P_{ij}) were estimated based on the rank order preference model (Equation 8). The fits were good based on Hauser's (1978) information theoretic test -- 80% of the total uncertainty was explained (U^2 = .795). The standard deviation between actual and predicted market shares was .9 share points. The logit model was not used since the preference measures collected here may not be interval scaled as required for this model. In this application, the collection of constant sum preference judgements which would allow ratio (or at least interval) scale estimates was infeasible since the number of paired comparisons across products for all uses would be an intolerable respondent burden. In cases where fewer use situations are present or where pretesting shows use situation not to be a basis of competition, constant sum procedures are practical. The rank order preference (Equation 8) model assumes the weak form of independence of irrelevant alternatives. McFadden, Train and Tye (1977) have developed a residual test procedure for the logit model (see **Appendix** Three for detailed description of test). We applied it here to the probabilities from the rank order preference model. Table 3 shows the chi-squared statistic associated with this test for the major products. In three cases (Maxwell House Ground, Maxim, and Taster's Choice caffeinated) violation of independence is indicated. In the other five cases, violation is not indicated.

Table 3 Test of Independence of Independent Alternatives

Product	χ^2(df=9)
Maxwell House Ground	17.1*
Taster's Choice (Decaffeinated)	5.6
Nescafe	11.7
Maxim	17.2*
Instant Maxwell House	3.3
Chock Full O'Nuts (Ground)	6.4
Taster's Choice (Caffeinated)	18.8*
Sanka (Instant)	11.0

* = significant at the 10 percent level

These results are mixed, but indicate the independence of irrelevant alternatives assumption may be violated. In a later section we test the sensitivity of the hierarchical branching to this assumption.

Hierarchical Definition of Market

In this section we describe the application of the branching procedure, consider heterogeneity in consumers' views of the competitive structure, examine the convergence obtained from the data on shopping in the laboratory store, and report a sensitivity analysis on heterogeneity and the possible violation of the assumption of independence of irrelevant alternatives.

First Level Branching: At the first level of the hierarchy, three branching hypotheses were tested based on product characteristics (see Figure 5). The ground/instant alternative passes the necessary tests ($P_b > R_b$ at 10% level and $\bar{P} > \bar{R}$ at 10% level). The caffeinated/decaffeinated alternative fails the necessary condition in the decaffeinated branch ($P_b \not> R_b$ at 10% level) and the brand structure fails in all branches. The best first level division is ground/instant; in it 71 percent of the respondents would buy another product in the branch where their first preference product resides if that most preferred product were not available. Use branching was evaluated by factor analyzing the matrix of the proportion of people who would consider products for each use (see Appendix Two for data) and then assigning products uniquely to the use branches. One dimension of use was found ($\lambda_1 = 6.45$, $\lambda_2 = .28$), and all uses loaded heavily on that dimension. This is not surprising since inspection of Appendix Two shows little variation in the proportions considering a given product across uses. If finer use classifications are considered and two dimensions are forced, the only use situation that loads heavily on the second dimension is the portion of supper use represented by dinner with guests (evoked by only 10 respondents). Branching by use was not indicated by the factor analysis. Prior grouping of occasions into two classes by time of day of use (A.M. and P.M.) was also evaluated. Brands were assigned to either an A.M. or P.M. branch based on whether they were most heavily evoked for A.M. or P.M. This branching failed the required test (P_{AM} = .29, P_{PM} = .27, R = .5). The absence of use as a major basis for defining the market was supported by the use panel which indicated 54% of the respondents used only one brand over all occasions in the week and 10% more used one brand for all uses until it ran out and then switched to a new brand for all subsequent uses. (See Laurent, 1978 for a more extensive discussion

Figure 5

First Level Branching - Product Characteristics

Alternative 1: Ground/Instant***

$\bar{P} = .71$ $\bar{R} = .49$

Ground***	Instant***
$P_b = .60$	$P_b = .76$
$R_b = .49$	$R_b = .49$
$N_b = 97$	$N_b = 198$

Alternative 2: Caffeinated/Decaffeinated ΔΔ

$\bar{P} = .64$ $\bar{R} = .49$

Caffeinated***	Decaffeinated Δ
$P_b = .74$	$P_b = .44$
$R_b = .49$	$R_b = .49$
$N_b = 195$	$N_b = 100$

Alternative 3: Brands ΔΔ

$\bar{P} = .07$ $\bar{R} = .143$

Maxwell House Δ	Tasters Choice Δ	Sanka Δ	Brim Δ	Folgers Δ	Nescafe Δ
$P_b = .09$	$P_b = .04$	$P_b = .07$	$P_b = .08$	$P_b = .04$	$P_b = .05$
$R_b = .15$	$R_b = .15$	$R_b = .15$	$R_b = .15$	$R_b = .15$	$R_b = .15$
$N_b = 99$	$N_b = 49$	$N_b = 49$	$N_b = 19$	$N_b = 15$	$N_b = 17$

Δ = model probability not significantly greater than random value (R_b) at 10 percent level.

ΔΔ = at least one branch fails requirement (Δ)

* = significant at 10% level
** = significant at 5% level
*** = significant at 1% level

of this data.) The shelf check indicated 43% had only one container of coffee on hand and 60.6% had only one container open. Although the usage situation is an important phenomena in understanding coffee consumption, it is not a good overall basis for hierarchically defining the competitive structure of products in the market.

A first level branch alternative based on user association of products was formulated by defining two branch segments based on their purchase rates (heavy--more than one purchase per two weeks, and light--one or fewer purchases per two weeks). Products were assigned to the branches where their evoking rate proportion was highest. This branching failed the necessary criteria in the light branch ($P_{HEAVY} = .65$, $P_{LIGHT} = .39$, $R_b = .49$, $\bar{P} = .53$, $\bar{R} = .49$). Further user segmentation was conducted by clustering individual responses to questions on coffee consumption (agree/disagree to 10 statements, e.g. : (1) If I'm only going to make one or two cups of coffee, I usually use instant coffee, (2) Sometimes, when a friend drops in, I prepare coffee in a different way from the way I prepare it for myself, and (3) I use decaffeinated coffee on those occasions when I'm concerned about being able to get to sleep afterwards.). After assigning products to one of the two segments, the branching probabilities were calculated and found to be below the random levels ($P_1 = .45$, $P_2 = .48$, $R_b = .49$).

<u>Second and Third Level</u>: The best first level branching considering product characteristics, uses, and users was ground versus instant coffee. Figure 6 shows second level branching from the first level ground/instant split. The branching of ground coffee into caffeinated and decaffeinated fails in the decaffeinated/ground branch. Both the division of instant into freeze-dried and regular branches and into caffeinated and decaffeinated branches pass the tests ($P_b > R_b$ & $\bar{P} > \bar{R}$ & $W_{b,bb} < R_{bb}$ at 10% level). The regular versus freeze-dried is better, but not significantly.

Figure 6

Second Level Branching

Alternative 1:

$\bar{P} = .51$ $\bar{R} = .32$

- Ground***
  - $P_b = .6$ $R_b = .49$
  - $N_b = 97$
- Instant***
  - Regular***
    - $P_b = .57$
    - $R_b = .24$
    - $N_b = 111$
  - Freeze Dried***
    - $P_b = .34$
    - $R_b = .24$
    - $N_b = 87$

Alternative 2:

$\bar{P} = .525$ $\bar{R} = .32$

- Ground***
  - $P_b = .6$ $R_b = .49$
  - $N_b = 97$
- Instant***
  - Caffeinated***
    - $P_b = .53$
    - $R_b = .24$
    - $N_b = 113$
  - Decaffeinated***
    - $P_b = .43$
    - $R_b = .24$
    - $N_b = 85$

Alternative 3:

$\bar{P} = .68$ $\bar{R} = .41$

- Ground $^{\Delta\Delta}$
  - Caffeinated***
    - $P_b = .58$
    - $R_b = .23$
    - $N_b = 82$
  - Decaffeinated $^{\Delta}$
    - $P_b = .194$
    - $R_b = .23$
    - $N_b = 15$
- Instant***
  - $P_b = .65$ $R_b = .49$
  - $N_b = 198$

Figure 7 indicates the third level branching of caffeinated and decaffeinated instant into freeze-dired and regular (Figure 6, Alternative 1) or freeze-dried and regular into caffeinated and decaffeinated (Figure 6, Alternative 2) is justified. This branching also passes the test that switching to the other branches be less than that branch's random probability.

Figure 7 shows the best branching. In this representation we use caffeinated and decaffeinated at the second level, but it should be recalled that freeze-dried and regular would also be acceptable. In either case, the end point branches are the same. The figure also shows the probabilities of buying when the first preference brand is available (PP and PP_b from equations 1 and 2 without restriction $j \neq j^*$). These values are high and indicate the expected proportion of next purchases in each branch without restricting the most preferred product.

Branching Based Only on Consideration Sets:

As indicated above, the probabilities of choice could be estimated by assuming each product in the consideration set other than the first preference has an equal probability of choice ($P_{ij} = (1-P_{ij}{}^*)/(n_i-1)$, where n_i is the number of products in individual i's consideration set). The branching procedure can be applied to these probabilities and compared to P_b and $\bar{P}$ obtained from Equations 8 and 9 which use information on preference as well as consideration set.

Figure 7 shows in parentheses the branching probabilities derived from the consideration set information. The values are surprisingly close and indicate most of the information utilized in the definition of the hierarchy is contained in the consideration set. Preference information improves the values, but branching based on consideration produces similar results.

Heterogeneity: Calculation of each individual's P_{ib} under the alternative first level branchings (see Figure 5) and assignment to the best fitting tree led to the identification of some differences in consumers' views of the competitive structure. Table 4 shows the number of people who fit one tree better than others.

Table 4 Heterogeneity in Competitive Structure

Dominant Tree	Number in Which One Tree Dominates	$\bar{P}$
1. Ground/Instant	84	.94
2. Caffeinated/Decaffeinated	53	.94
3. Brand	1	.85

The value of $\bar{P}$ indicates that groups described by ground/instant and caffeinated/decaffeinated branchings fit their respective branchings significantly better than in the homogeneous case (see Figure 5). These two groups represent significant heterogeneity while the remaining 60 percent of the sample are not better described by one tree than others. (Eight-four people were equally well described by Alternatives 1 and 2, 6 people by Alternatives 2 and 3, and 6 people by Alternatives 1, 2, and 3.)

The group best described by the caffeinated and decaffeinated structure (Alternative 2 in Table 4) were subjected to second level branching. In the caffeinated branch, attempts to branch (ground/instant and by brands) failed to meet the required criteria ($P_b > R_b$ and $W_{b,bb} < R_{bb}$). Second level splitting of the decaffeinated branch was not possible due to small sample sizes. In applications where heterogeneity is present, larger initial samples should be collected or supplemental sampling conducted if heterogeneity is critical to the entry strategy decision. The sensitivity of entry strategy to the observed heterogeneity will be discussed in a subsequent section.

Convergent Analysis

The trees evaluated based on preferences and past choices and shown in Figures 5, 6, and 7 were tested by repeating the branching procedure with probabilities (P_b') measured by the proportion of people who purchased in the lab when their first preference product was not available. The analysis of the shopping data indicated that the tree in Figure 7 was the best. In Table 5 the probabilities from the preference analysis, shopping measures, the Bayesian update of the probabilities (Equation 10), and the random probabilities are shown. The values from the two analyses are similar. For example, for ground coffee, the preference analysis indicates 60 percent of people who have a first preference for a ground product would buy another ground if their first preference was not available; in the lab, 60 percent of these people actually bought another ground when their favored brand was out of stock. This close correspondence was not found within the instant branches where substantial differences were observed, but the updated values (P_b'') pass all the significance tests (P_b'' greater than R_b at the ten percent level) and continue to indicate the tree in Figure 7 as the best hierarchical description of the market.

Perceptual Maps

Perceptual maps were generated for each of the five end point branches in the tree. Figures 3 and 4 and their associated discussions have presented the factor analysis results and perceptual maps for the caffeinated/regular/instant and caffeinated/freeze-dried/instant branches. Figures 8, 9, and 10 show the perceptual maps for the remaining branches in the best tree (Figure 7). Next, we consider the implications of these maps and the hierarchical market definition for the formulation of entry strategy.

Figure 7

Best Hierarchical Description of Coffee Market

Coffee***

$\bar{P}$ = .71 (.70)
PP= .93
$\bar{R}$ = .49
N = 295

Ground***

P_b = .6 (.59)
PP_b = .91
R_b = .49
N_b = 97

Instant***

P_b = .76 (.76)
PP_b = .95
R_b = .49
N_b = 198

Caffeinated***

P_b = .53 (.55)
PP_b = .89
R_b = .24
N_b = 113

Decaffeinated***

P_b = .43 (.39)
PP_b = .9
R_b = .24
N_b = 85

Regular***

P_b = .38 (.39)
PP_b = .86
R_b = .11
N_b = 68

Freeze Dried***

P_b = .22 (.18)
PP_b = .84
R_b = .11
N_b = 45

Regular***

P_b = .30 (.25)
PP_b = .89
R_b = .11
N_b = 43

Freeze Dried***

P_b = .24 (.22)
PP_b = .85
R_b = .11
N_b = 42

( ) = values of branching probabilities estimated from consideration set information only.

Figure 9

Perceptual Map For

Decaffeinated/Regular/Instant Coffee

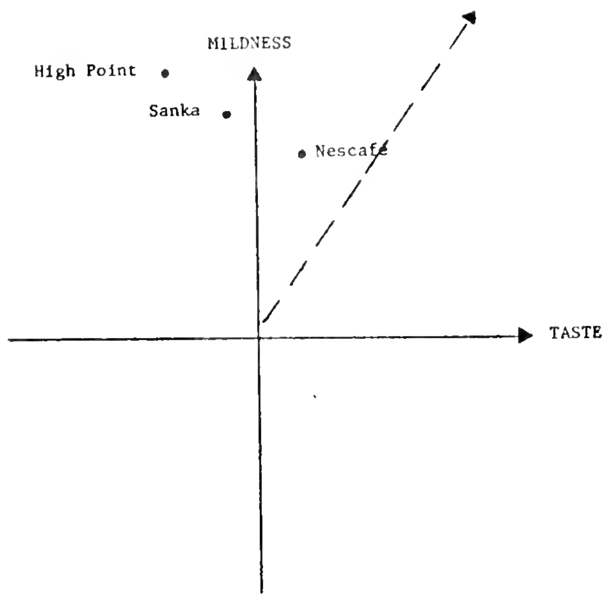
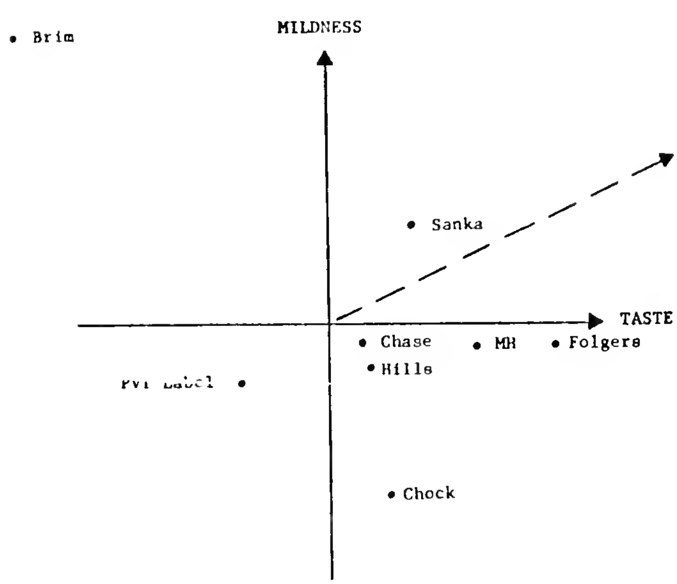


Figure 10

Perceptual Map For Ground Coffees



Entry Analysis

With a clear understanding of the hierarchical structure of competition and the positioning of products within each market, the next task is to calculate the potential profit for a new entrant and balance it against risk and investment considerations in making an entry commitment.

Profit, Investment, and Risk: Table 6 depicts the calculation of profit in each market. Sales volumes were based on 1977 U.S. warehouse sales withdrawal data and, because population growth is balancing approximately the slow decline in per capita consumption, it is assumed that no significant growth will occur in the future. Share potential is calculated by applying the entry model (Equation 12). Recall these share potentials assume good positioning on the market maps (maximum of existing attributes). The entry order (e) was determined by presuming we are considering a major market entry. Therefore, the major brands in each market were counted along with an aggregate product to reflect existing regional and small brands (e = 5 for ground, e = 5 for instant/caffeinated/regular, e = 3 for instant/caffeinated/freeze-dried, e = 4 for instant/decaffeinated/ regular, and e = 4 for instant/decaffeinated/freeze-dried).

The share potentials vary from 3.5% to 12.8%, but the markets are of different size and have different prices/pound. Dollar sales volumes were based on an average retail price of $3/pound for ground coffee and $8/pound for instant coffees. The greatest sales potential is for a ground coffee (70 million dollars) and the lowest for freeze dried, decaffeinated, instant (8 million dollars). Net contribution profit was simply calculated by assuming profit as ten percent of sales. This is a subjective estimate based on the assessment of the margin and competitive pricing practices in the industry.

Investment includes the expected development cost (Table one - note 3), investment in production facilities, and introductory marketing expenditures. The production investment is an estimated incremental expenditure to an existing facility to produce the new volumes required. If a firm now had no coffee production capability, the required expenditure could be much higher. On the other hand, if excess capacity existed in a facility, it would be much lower. The introductory marketing expenditure for advertising and promotion is based on twenty percent of the long-run annual sales revenue and is set to be consistent with past major national brand introductions.

The highest investment and profit potential are for a ground coffee. To compare return and investment, the simple payback period could be calculated. Ground coffee pays back the fastest (2.5 years based on the mature profit level), regular/caffeinated/instant in less than three years (2.8 years), and freeze-dried/decaffeinated/instant has the longest pay back (6 years). The others pay back in three to four years.

Payback is indicative of return on investment, but does not reflect risk considerations or the time value of money. To include these factors, discounted profit was calculated at a target rate of return of 20 percent (see Equation 17). The yearly profit was based on an eight year life cycle in which sales grow to full potential over the first two years (year one--50% of potential and year two--67% of potential), stabilized at full potential for four years, and then fall over the last two years (year seven--67% of potential and year eight--50% of potential). The total investment was divided by the total discounted profit. Based on this ratio, a share potential was found where the discounted profit just equaled the investment (ratio = 1.0). This break even ROI share was compared

Table 5

Lab Shopping and Updated Branching Probabilities

	Choice Model P_b	Shopping Observations P'_b	Updated P''_b	Random R_b
Ground	.60	.60	.60	.49
Instant				
Caffeinated/Regular	.38	.25	.32	.11
Caffeinated/Freeze Dried	.22	.24	.23	.11
Decaffeinated/Regular	.30	.21	.27	.11
Decaffeinated/Freeze Dried	.24	.32	.29	.11

Figure 8

Perceptual Map For

Decaffeinated/Freeze-Dried/Instant Coffees

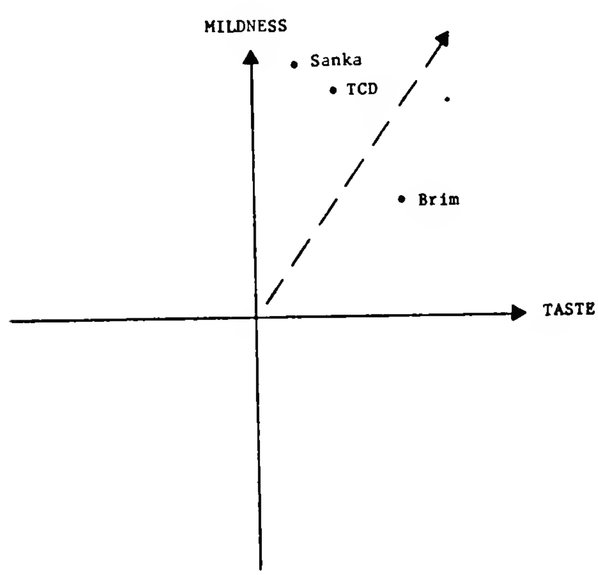


Table 6 Entry Analysis of Coffee Market

	Ground	Instant			
		Caffeinated		Decaffeinated	
		Regular	Freeze Dried	Regular	Freeze Dried
Volume (Millions of Pounds)	663	88	29	24	21
Entry Share Potential in Market	3.5%	6.2%	9.3%	12.8%	5.0%
Revenue - Ongoing (millions of dollars)	70	44	22	25	8
Profit - Ongoing (millions of dollars)	7	4.4	2.2	2.5	.8
Investment					
Development	2.7	2.7	2.7	2.7	2.7
Production	.5	.5	.5	.5	.5
Introductory Marketing	14.0	8.8	4.4	5.0	1.6
TOTAL	17.2	12.0	7.6	8.2	4.8
Probability of Achieving 20% Rate of Return	80%	70%	45%	45%	10%

to the expected share potential. Subjective estimates of exceeding the breakeven ROI share were made in each market based on the margin of safety (share potential less breakeven ROI share) and the assessment of the risk in entering each market. These values are equivalent to the probability of exceeding the target rate of return.

Entry Opportunities: Table 6 shows that the best chance (80%) for making 20 percent ROI is in the ground coffee market. Examination of the map for ground coffee (Figure 10) indicates the positioning opportunity is for a "mild" coffee with "good taste." A partially decaffeinated ground coffee might be the basis of combining the mildness of Sanka and the taste of Folger's brands. The caffeinated/regular/instant market also is attractive to entry since there is a 70 percent chance of achieving the target rate of return by investing in it. The positioning opportunity again is based on combining mildness and taste (see Figure 3). The freeze-dried/decaffeinated/instant market is the least attractive with only a ten percent chance of financial success.

The appropriate entry strategy for a company depends upon what products the firm now offers. Table 7 shows the existing brands (1977) of' three major manufacturers. If Nestle is considered, there is a clear match between the ground coffee entry opportunity and their existing product line since they now offer no ground coffee. On the other hand, General Foods already has many and perhaps too many ground coffee offerings. It has covered all the markets and its strategy for innovation should be based on revolutionizing the category. For example, a pre-brewed liquid coffee in a one-cup container that could be heated in a micro-wave oven might be the basis of creating a new market branch. Such a revolutionary strategy would be risky, but if General Foods wanted to grow in the coffee

Table 7

Brand Offerings by Selected Firms

	Ground	Instant			
		Caffeinated		Decaffeinated	
		Regular	Freeze-Dried	Regular	Freeze-Dried
Nestle	No Brand	Nescafe	Tasters' Choice	Nescafe	Tasters' Choice
Procter & Gamble	Folgers'	Folgers'		(High Point)	
General Foods	Maxwell House Sanka Yuban Brim	Maxwell House Yuban	Maxim	Sanka	Sanka Brim

market, this analysis suggests rather than looking for new positionings in the existing market, it should allocate effort to a major innovation to create new branches in the market structure. Procter and Gamble entered the market with Folgers' brand in the two most desireable markets--ground and caffeinated/regular/instant. At the time of this research, P & G had "High Point" test market. Our analysis would have suggested a 45 percent chance for a new decaffeinated/regular/instant market entrant to be financially successful.

Sensitivity to Heterogeneity: The entry opportunities were identified based on an assumption of homogeneity in consumers' view of the competitive market structure. As indicated in a previous section, 18 percent of the sample see the market differently. These people consider the market divided into two branches--caffeinated and decaffeinated. The new ground coffee and caffeinated regular instant coffee opportunities would enter in their caffeinated branch. In this branch, all caffeinated brands compete, and the new entry would have many competitors (10 major products). The new product entry would be the eleventh entry in the market, and it could not expect to get a large share of this crowded market. The entry index (Equation 15) for the eleventh product would be .05. This inference is beyond the range of the data used to estimate the index, and in our opinion, may understate the potential, but we will use it in this calculation to determine sensitivity to heterogeneity. If the positioning (S/S^*) is equal to the first product in this caffeinated market, the entry potential share (Equations 12 and 13) would be 1.15 percent.

This share is lower than in the homogenious case (3.5 percent for ground, 6.3 percent for instant), but the caffeinated market is larger than the ground or caffeinated/regular/instant branches. The weighted average total sales for a new ground coffee would be \$63 million (\$57.4 million from the 82% represented by Figure 7 and \$6 million from the 18% who had a caffeinated/decaffeinated branching). The sales for the new caffeinated regular instant would be \$42 million (\$36 million from the 82% and \$6 million from the 18%). The probability of achieving the ROI for a new ground coffee would drop to 70 percent and remain almost unchanged at 67 percent for a new caffeinated/regular/instant.

The effect of heterogeneity in this application is to increase the estimated risk, but the entry strategy remains unchanged. In other cases, decisions may be sensitive to heterogeneity and suggest the need for different new product entries. Representing the heterogeneity by different trees and calculating the weighted average sales volume and profit provides a basis for evaluating strategies under heterogeneous conditions.

<u>Sensitivity to Assumption of Independence of Irrelevant Alternatives</u>: As indicated earlier, McFadden's test of residuals suggest violation of the independence of irrelevant alternatives may have occurred (Table 3). In order to determine the sensitivity of our hierarchical specification to this potential violation, we re-estimated the choice probabilities (P_{ij}) and the branching probabilities by hierarchical logit procedures (McFadden, 1980).

The use of the hierarchical logit model requires that we assume our preference measures (7 point) are interval scales. To investigate the effect of an interval scaling assumption, we compare the rank order preference and standard multinomial logit model in which the interval property is also necessary. The correlation of the choice probabilities (P_{ij})

estimated by the rank order model (Equation 7) and multinomial logit model (Equation 8) were highly correlated (ρ = .965), so the probability estimates do not appear to vary much when the interval scaling property is assumed.

The correlation of the probabilities from the hierarchical logit to those from the multinomial logit model in the ground/instant structure was .84. This is not as high as the previous correlation and use of the probabilities from the hierarchical logit led to different branching probabilities (P_b). For example, the branching probability for the ground coffees was .42 -- less than the random value of .49 This would suggest rejection of the first level branching previously indicated (Figure 6). However, before reaching this conclusion, recall that heterogeneity is present (see Table 4).

In order to investigate the effect of heterogeneity on hierarchical logit estimation, the hierarchical and multinomial logit probability estimates were obtained within the two heterogeneous groups--ground/instant (n=84) and caffeinated/decaffeinated (n=53). Despite the small samples, within these groups the correlation returned to high levels (ρ=.96 for the ground/instant group and P=.91 for the caffeinated/decaffeinated group) and the branching probabilities were high (ρ= .84 for the ground/instant group and $\bar{P}$ = .75 for caffeinated/decaffeinated group). These findings suggest extreme caution should be excercised in applying hierarchical logit procedures when heterogeneity is possible, since it appears to bias the estimates.

Once heterogeneity is considered, the sensitivity to possible violation of the assumption of independence of irrelevant alternatives is low since the hierarchical and non-hierarchical logit procedures yield very similar probability estimates (P_{ij}). This result combined with the low managerial sensitivity to heterogeneity indicated in the previous section suggest the overall hierarchical tree and maps are appropriate for entry strategy formulation in the case presented here.

The absence of an empirical problem with the independence of irrelevant alternatives can be explained in part by the research design which measures preferences only over individual consideration sets (C_i). The consideration set is the consumer's self-screening of the alternatives and the designation of those "relevant" to his or her choice. The empirical analysis here is consistent with the notion that a Luce model describes individual choices across the consideration set and that the hierarchy is primarily the result of aggregation of such individual Luce models rather than the sum of individual hierarchical choice models.

Limitations of Application: This study was conducted to test and demonstrate the model and measurement methodology. Care should be exercised in taking specific marketing actions based on it since the sample is not representative of all regions of the U.S., and many financial estimates were made in calculated return on investment. In a company sponsored application, the approximate sample size could have been 1,000 respondents across 5 or 6 cities. This study was not sponsored by a manufacturer, so the sample was smaller and for research purposes only. The sample was collected (July - August, 1977) after a period in which coffee prices rose from two to four dollars per pound and then stabilized at three dollars a pound. It would be necessary to repeat the study under the current price and product competitive environment before it could be used in planning strategy in today's market. Another caution is reflected in the margin and investment assumptions. These are subjective estimates and should be based on actual company cost, market prices, and facilities requirements before a firm contemplates utilizing the results in committing to designing a new product entrant into the coffee market.

RESEARCH ISSUES

This paper has presented a model and measurement methodology to estimate a hierarchical structure of competition and examine its implications for market entry strategy formulation. In its first application it produced encouraging statistical significance and managerial insight; however, several technical issues require further research.

One method has been proposed in this paper for hierarchical definition of a market. It would be useful to conduct a comparative empirical study to see if it is more powerful than other methods (see discussion of alternative approaches) in identifying the hierarchical structure of competition.

The entry model proposed here (Equation 12) demonstrated statistical significance, but research could be directed at improving it. The model now represents entry share by a proportionality to the first product in the market, and thereby, does not consider other products. Attention should be directed at extending this model to include the shares of all previous entrants, so their defensive reactions could be explicitly considered. It also would be productive to model entry not only by an order interger, but also by the time (months) between successive entries. If the second product in a market enters one month after the first, the effect is likely to be different than if the entry is 12 months after the first product. Finally the index (E_e) includes all effects except positioning. It could be subdivided to consider phenomenon such as advertising and promotion expenditures.

A third technical issue in the model is what to do if only one product defines a competitive market branch. In this case, the model criterion based on switching is meaningless. A single product branch would be indicated if consumers would consider that product as the only acceptable alternative for a specific use. In terms of our measures, a consideration set of one brand and a large proportion of respondents refusing to buy in the laboratory store would indicate this condition. Research is needed to improve procedures for identifying and testing single product branches, but in practice, such branches are not often observed because competitors usually develop quickly if the product is successful.

A final area of research is consideration of durable consumer, industrial, and service industries. The application reported here was a frequently purchased consumer product. The model criteria based on preferences and consideration sets could be applied to other industries, but the laboratory procedures would be inapplicable to industrial and service purchases. Shopping for consumer durables would be possible by the use of lottery (e.g., one in n chances to win the product of your choice, or cash), but realism is lost. Another problem is the estimation of choice probabilities. If the product is a first time purchase, the logit model which uses last purchases and preferences to estimate probabilities could not be used. Direct estimates of probabilities of purchase from consumers (Juster, 1966, and Morrison, 1979) or the assumption of equal probabilities over the consideration set could be used to provide estimates of probabilities, and thereby, allow application of the branching procedure. The branching based on consideration sets reported here (see Figure 7), indicate this approach may be feasible.

New applications are underway in several frequently purchased consumer brand markets to further assess the empirical adequacy of the model and its managerial relevance. Testing in the consumer, industrial, and service industries is anticipated. If statistical and managerial significance is achieved, the proposed model will be a useful tool aid in market entry strategy formulation.

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APPENDIX ONE

Mean and Variance of Purchasing in Branch*

First the distribution is established at the individual level (Lemma 1) and then aggregation under homogeneity is considered (Lemma 2). The theorem establishes the formulas for desired mean and variance with heterogeneity across individuals.

Lemma 1: If $\underline{X} = (X_1, \ldots X_k)$ are multinomially distributed random variables with parameters n=1 and $\underline{\mathbf{p}}=(p_1,\ldots,p_k)$, then $y_s = \Sigma_S X_k$ is a Bernoulli random variable with parameter $p_s = \Sigma_S p_k$ where the set S is a subset of the original random variables.

Proof: The probability distribution for $\underline{X}$ is given by

$$f(\underline{X}|1,p) = \prod_{k=1}^{k} p_k^{X_k} \qquad \text{for } X_k = 0,1, \quad \sum_{k=1}^{K} X_k = 1$$

$$0 \text{ otherwise}$$

Since the X_k are (0,1) r.v. and since $\Sigma_k X_k = 1$ we know that y_s is a (0,1) r.v. Furthermore $y_s = 1$ iff $X_k=1$ for $k\varepsilon S$. Since the events $X_k=1$ are mutually exclusive we have that the probability that $y_s = 1$ is given by

$$\text{Prob}\{y_s=1\} = \sum_{k\varepsilon S} \text{Prob}\{X_k=1,\ X_j=0,\ j\neq k\} = \sum_{k\varepsilon S} p_k = p_s$$

Similarly,

$$\text{Prob}\{y_s=0\} = \text{Prob}\{X_k=0 \ \forall\ k\varepsilon S\} = \sum_{k\notin S} \text{Prob}\{X_k=1, X_j=0, j\neq k\}$$

$$= \sum_{k\notin s} p_k = 1-p_s$$

This is the definition of a Bernoulli random variable. Q.E.D.

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* These proofs were supplied by John R. Hauser and are gratefully acknowledged.

Lemma 2: Let $\underline{X}$ be a vector multinomially distributed random variable with parameters 1 and p. Let $y_s = \sum_S X_k$. Let m = the number of times $y_s=1$ on n successive independent draws. Then m is a binomial random variable with parameters n and p_s where $p_s = \sum_s p_k$.

Proof: By lemma 1 y_s is a Bernoulli random variable with parameter p_s. Since the successive draws are independent, m is a binomial random variable with parameters n and p_s. For example see Drake (1967, p. 129). Q.E.D.

The probability distribution of m is given by:

$$f(m|n,p_s) = \begin{cases} \binom{n}{m} p_s^{\,m}(1-p_s)^{n-m} & m=0,1,\ldots,n \\ 0 \text{ otherwise} & \end{cases}$$

Theorem 1: Let $\underline{X}_i = (X_{1i}, X_{2i}, \ldots, X_{ki})'$, i=1 to I, be a series of independent random variables each a multinomial random variable with parameters n_i (the number of successive draws for i) and $\underline{p}_i$. Let S be a subset of the indices 1 to K. Let $y_{si} = \sum_S X_{ki}$ and let $Y_s = \sum_{i=1}^{I} y_{si}$. Then for large I and for $\underline{p}_i$ not uniformly skewed, Y_s is approximately normal with variance $\sum_{i=1}^{I} n_i p_{Si}(1-p_{Si})$ where $p_{Si} = \sum_S p_{ki}$ and mean $\sum_{i=1}^{I} n_i p_{Si}$.

Proof: Y_s is approximately normal by the central limit theorem (Drake, 1967, p. 212), since Y_s approaches normality as I increases without bound. Independence and not uniformly skewed are the conditions necessary for the CLT. The variance and mean are computed by summation since the random variables are independent (Drake, 1967, p. 108). Q.E.D.

Corollary 1: Let $\underline{X}_i$ be a series of independent multinomial random variables with parameters n_i and p. Let S be a subset of the indices 1 to K. Let Y_s be defined as in theorem 1. Then Y_s is approximatley normal with variance $(\sum_{i=1}^{I} n_i)\ p_s(1-p_s)$ and mean $(\sum_{i=1}^{I} n_i)\ p_s$, where $p_s = \sum_s p_k$.

Proof: The result follows directly from theorem 1 with the substitution of $p_{si} = p_s$ for all i. Q.E.D.

Corrollary 2: Let $\underline{X}_i$ be a series of independent multinomial random variables with parameters n_i and p. Let $p' = Y_s/I$ where Y_s is defined by theorem one. Then the variance of p' is

$$\sum_{i=1}^{I} n_i p_{si}(1-p_{si})/I^2$$

Proof: It is known that the variance of ax, where x is a random variable is a^2 times the variance of x (Drake, 1967, p. 112). Let $a=1/I$ and $x = Y_s$. Then the variance of Y_s/I is $1/I^2$ times the variance of Y_s or

$$\sum_{i=1}^{I} n_i p_{si}(1-p_{si})/I^2 \text{ .} \qquad \text{Q.E.D.}$$

APPENDIX TWO

Use Data

In interviews with 295 coffee drinkers (greater than one cup per day), 808 uses were evoked across six major use classes (average is 2.7 uses per person). Table A-1 shows the proportion of the respondents who evoked each use and the proportion who evoked given brand for those who evoked given use. For example, 8.5% of the respondents who evoked breakfast as a use evoked Brim (Instant) as a product for this use.

Table A-1

Use and Brand Consideration by Occasion

	Breakfast	Day Alone	Day Others Present	Lunch	Supper	Evening
Percent Evoking Use	96.3	41.7	23.4	30.2	43.7	43.1
Percent Who Would Consider Brand:						
Brim (Instant)	8.5	6.5	12.1	7.9	8.4	7.1
Folger (Instant)	6.3	6.5	3.0	6.7	6.7	6.3
Folger (Ground)	7.7	9.8	9.1	3.4	5.9	7.9
Maxwell House (Instant)	32.0	26.8	40.9	36.0	33.6	27.6
Nescafe	10.6	11.4	18.2	9.0	8.4	15.0
Nescafe (Decaf)	10.6	8.9	6.1	12.4	10.1	7.1
Maxim	12.0	15.4	7.6	13.5	13.4	11.8
Taster's Choice	20.1	18.7	24.2	20.2	18.5	22.0
Taster's Choice (Decaf)	13.0	17.1	16.7	20.2	17.6	17.3
Sanka (Instant)	22.9	22.0	18.2	21.3	20.2	24.4
Sanka (Freeze-Dried)	7.7	8.1	9.1	12.4	11.8	3.9
Sanka (Ground)	6.3	7.3	12.1	5.6	9.2	4.7
Chock Full 'O Nuts	10.6	8.9	10.6	6.7	8.4	9.4
Hills Brothers	7.0	4.1	1.5	3.4	6.7	1.6
Maxwell House (Ground)	28.9	32.5	24.2	29.2	32.8	26.0

APPENDIX THREE

McFadden, Train, and Tye Test for Independence of Irrelevant Alternatives

McFadden, Train and Tye (1977) have suggested a chi-squared test of association for the logit model which was applied here to the probabilities obtained from the rank order preference model. The procedure begins by considering all individuals who have included alternative k in their choice sets. The individuals are then sorted in decreasing order of their probability of choosing k. The list of individuals is then sequentially subdivided into m cells with N_m individuals in each cell (i.e., take the first 10 in the list and form cell 1, the next 10 and form cell 2, etc.).

For each individual in the list, there is a 0-1 variable indicating whether in an observed choice situation the individual chose alternative k. A non-negative residual is generated whenever an individual actually chose k, since that individual's probability of choosing k is $0<P_{ik}\leq 1$ and $1-P_{ik}\geq 0$. Similarly, a negative residual is generated when the individual did not actually choose alternative k.

Within each cell for a particular alternative k, the number of non-negative and negative residuals are tabulated, and the average probability of choosing k is computed. The data for a particular alternative would be organized as follows:

Table A-2

Cell	Number of Residuals: Non-Negative	Number of Residuals: Negative	Average Probability ($\bar{P}_{ij}$)
1	18	7	0.74
2	21	4	0.73
3	19	6	0.71
etc.			

By construction, we might reasonably expect the number of non-negative residuals per cell to be highest in the lowest numbered cells, since where the average choice probability is higher, more people should be expected to have chosen alternative k in the observed choice situation.

The chi-squared test proposed by McFadden <u>et al</u> determines if the pattern of non-negative residuals is significantly different from that which would be expected given the average choice probabilities. McFadden reasons that this would occur in situations where the independence of irrelevant alternatives property is violated.

The chi-squared test of association for alternative j is:

$$\chi^2 = \sum_{m=1}^{M} (S_m - N_m \bar{P}_{jm})^2 / N_m \bar{P}_{jn}$$

m = index of cell

M = total number of cells

S_m = number of positive residuals in cell m

N_m = total number of observations in cell m

$\bar{P}_{jm}$ = average probability of choosing alternative j in cell m

$\bar{P}_{jn}$ = average probability of choosing alternative j in in the total sample of individuals who included j in their choice set.

The chi-squared statistic is in this case bounded by M-1 d.f. and M-K-1 d.f., where K is the number of parameters estimated in the choice model.

In the case reported in Table 3, 10 cells were formed for each of the major brands of coffee tested. The chi-squared test is bounded by 9 and

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8 d.f., with critical values of 14.7 and 13.4 respectively at the 10% confidence level. If the test statistic for a particular alternative exceeds the critical value at 9 d.f., there is a clearly significant difference in the observed pattern of residuals versus the expected pattern. Similarly, if the test statistic is below 13.4, the observed is not significantly different from the expected. Values of the test statistic between 13.4 and 14.7 yield inconclusive results.

Table 3 shows the chi-squared statistic for the major products. In three cases (Maxwell House Ground, Maxim, and Taster's Choice caffeinated) significant statistics indicate possible violation of the IIA property.

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