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An evaluation of research methodologies for benefit segmentation analysis.

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AN EVALUATION OF RESEARCH METHODOLOGIES FOR BENEFIT SEGMENTATION ANALYSIS

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AN EVALUATION OF RESEARCH METHODOLOGIES
FOR BENEFIT SEGMENTATION ANALYSIS

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ABSTRACT

This study examines the methodological considerations relevant to benefit segmentation. The scenario chosen was the retail banking market in a large midwestern city where six banks controlled virtually all retail banking activity within a closed economic environment.

Using past benefit segmentation studies as a guideline, the methodological steps of a typical procedure to segment consumers based on benefits sought from the product class/ retail outlets was evolved. After a detailed examination of the procedures, as well as consideration of other methodological advances in segmentation and general consumer research, several research questions were formalized. The three main questions were:

1. Which data input procedure is the most consistent and gives the clearest solution in benefit segmentation analysis?

2. In the benefit segmentation context, what rules should govern the choice of clustering algorithm, and how sensitive is the solution to algorithm choice?

3. Is the solution stable over time?

Data was collected on the retail banking market from a consumer panel in two waves, two years apart. Four data input types were submitted to the analysis, which was wholly in a split half design, to act as a check for consistency validity.

Factor scores of individual's benefits sought vectors were chosen as the data input type due to greatest consistency, orthogonality, reduced redundancy of measure, and potential for avoiding statistical assumption violation in testing for cluster differences.

Three clustering algorithms were evaluated in several ways for consistency over split halves. Also properties of monothetic versus polythetic algorithms were exemplified and judged against criteria of vagueness of solution and managerial usefulness. The Howard-Harris routine was selected according to the above criteria and market segmentation solutions were presented for each time period which were managerially useful and verifiable by other measures.

Classification rules were derived via multiple discriminant analysis and the rules were very successful. Using crossed split half predictions, an average of 86 percent of all known consumers were correctly classified in each time period. The comparative static analysis revealed only a slight demographic change over the two year time period.

Thus at the segment level no change was apparent and no advertising copy policy change based on benefits sought was warranted.

Further investigation revealed a "cluster switchers" phenomena where the individuals changed their set of benefits sought in such a way so as to switch groups. Differential loss from groups was not apparent, but 71.2 percent of individuals switched groups over time. Thus, although the relative desirability of various benefit bundles remained constant, the individuals seeking those sets of benefits changed.

The three major research questions were successfully operationalized and answered. The result of the dynamic analysis leads to further theoretical investigation into the sensitivity of individuals to endogenous and exogenous market forces which cause changes on the benefits sought vector. At present, static copy platform advertising policy and changing media targeting are implied, but the latter is on weak footing especially in local markets without a more detailed structure to handle an obviously dynamic market structure.

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CHAPTER I

INTRODUCTION

Motivation

In the ninteen years since Wendell Smith (1956) introduced the concept of market segmentation to the field of marketing, much research effort and discussion have been focused on the problem of segmenting markets. Specifically, market segmentation can be viewed as the division of a market into segments or groups of buyers, to permit the development of specific marketing mixes for each group to attain some objective, such as maximization of profits or market penetration, than would be possible by recognizing or assuming the market to consist of homogeneous buyers.

The literature on the subject is quite large and includes viewpoints directed toward normative theory, consumer psychology, and marketing policy as well as lending insight to such other concepts as product positioning. In practice, it is extolled for its success by managers and consultants alike and has been so popularized as to be included in practically all basic marketing courses and texts.

Professional marketing analysts have claimed success in applying market segmentation mainly in a consumer goods context. Very few of the studies, done with a managerial orientation, have clearly outlined their methodology and are almost never published for fear of losing a competitive advantage for the firm or client.

This dissertation will report the results of a managerially oriented segmentation study and will carefully lay out the procedures and the relevant methodological considerations. Also, the results will be checked for stability over time and the implications for marketing strategy. In order to better define the limits of the study, several views of segmentation will now be considered.

Segmentation Defined

Wendell Smith's (1956) ground breaking article led to a recognition of "diversity of demand" as a market characteristic. The economic theory of market segmentation evolved much earlier from the theoretical development of monopolistic competition by Joan Robinson (1954) and Edward Chamberlain (1933). In revitalizing the classical theories of "perfect" competition Robinson and Chamberlain provided explanations of diversity of supply and demand within a market. Despite the fact that in the 1930's, there was an increasing variety in the output of goods and services, their explanations were frequently ignored in practice. Perhaps this can be explained by the lack of discretionary income and "funds for search" on the part of buyers. Hence, it made little sense for producers to treat consumers in other than a nondifferentiated way.

After World War II there was a pent up demand for durables, and manufacturers could continue to offer items without regard to consumer preferences regarding colors, sizes, and other options and features that became important to buying decisions in the late 1950's and 1960's. By the mid 1950's it was becoming evident that the strategy of demand convergence or product differentiation (market aggregation) was not always an answer. This strategy refers to the use of a single product offering to the market accompanied by a promotional (package, advertising, pricing) campaign to distinguish "each" product in the line. Thus, the manager would not really react to the differences in demand but rather would encourage invidious comparisons between products which are virtually identical.

This was the setting for Smith's (1956) classic article which stated for certain cases "it is better to accept divergent demand as a market characteristic and to adjust product lines and marketing strategy accordingly." Thus, it is a merchandising strategy where a product is matched to the desires of one or more market segments. Thus, product differentiation gave way to market segmentation where marketing programs were based on the measurement and definition of market differences.

Managerially, market segmentation implies the need to uncover groups whose demand curves differ and then to match the offering(s) of the firm to those groups. Such an approach would logically suggest the microeconomic model of price discrimination. The theory of price discrimination points out the necessity to define segments with demand curves that differ according to price and promotion responsiveness. The optimum strategy is to allocate promotion expenses and set price for each segment where marginal revenue equals marginal cost, or where incremental returns are equal across segments (Massy, 1970).

Price Theory Model

The general model of price discrimination is well known to many and will be only briefly explained here as a prelude to the more complex model which includes promotion.

In the simple model we will assume there are two market segments, each segment has a different demand function, it is possible to charge different prices to each segment, and buyers in the lower priced segment will not sell to buyers in the higher priced segment. One could imagine that separation need not be logistical but could be due to a moderate amount of product differentiation so that the actual or perceived substitution effects are small.

In this simple model, we will assume linear demand and costs.

$$\text{Demand:} \quad p_1 = 360 - 10a_1$$

$$p_2 = 160 - 5q_2$$

Cost: $TC = 100 + 40(q_1 + q_2)$

Revenue: $TR_1 = p_1q_1 = 360q_1 - 10q_1^2$

$TR_2 = p_2q_2 = 160q_2 - 5q_2^2$

Profits are maximized when marginal revenue in each market is equal to the marginal cost:

$$MR_1 = \frac{d\ TR_1}{d\ q_1} = 360 - 20q_1 = MC = 40$$

$$q_1 = 16$$

$$MR_2 = \frac{d\ TR_2}{dq_2} = 160 - 10q_2 = MC = 40$$

$$q_2 = 12$$

The prices, total revenues, costs, and net profit are easily determined by substitution.

Thus: $p_1 = 360 - 10q_1$

$p_1 = 360 - (10 \times 16) = 200$

$p_2 = 160 - 5q_2$

$p_2 = 160 - (5 \times 12) = 100$

$TR_1 = p_1 \times q_1$

$TR_1 = 200 \times 16 = 3200$

$TR_2 = p_2 \times q_2$

$TR_2 = 100 \times 12 = 1200$

$\pi(\text{Profit}) = TR_1 + TR_2 - TC$

$\pi = 3200 + 1200 - (100 + 40(28)) = 3180$

Thus, the price discriminator takes advantage of the different degrees of product demand in the two markets, as expressed by the different demand curves.

As an interesting corollary, let us examine the profit to the firm when only one aggregate demand curve is recognized.

Solving the original demand curves for quantity yields:

$$q_1 = 36 - 1p_1$$

$$q_2 = 32 - 2p_2$$

If the prices in the two markets are to be equal, then both equations are summed to yield:

$$q = q_1 = q_2 = 68 - .3p$$

Applying the usual maximization procedure as above yields:

$$q = 28$$

$$p = 93.3$$

$$TR = 2612.40$$

$$\pi = 1392.40$$

Thus, the profit realized when ignoring demand differences is substantially lower. For an extended treatment where costs and demand curves are not lienar, see Henderson and Quandt (1972).

Price discrimination has been employed in various ways. The well known strategy of market skimming is a variation of this where a high initial price accompanies a product introduction followed by gradual price reduction as the product matures.

If the initial price exceeds marginal costs and the rate of price decline is greater than the decline in marginal costs (which usually fall with increased volume and worker's learning curves), the policy is market segmentation by price discrimination. Those consumers with a high need for the product are induced to buy first at the higher price; then customers with less need are added, and so on. Price discrimination thus occurs over time rather than over groups at a particular time. These temporal segments usually contain members who are self-selected rather than by the targeting of special product promotion or availability.

Price Theory Model With Promotion

Palda (1969) presented a model which extended the simple price model to include advertising and product quality (one dimension on which products can be differentiated). Product quality is not relevant unless it can be varied over segments. Also, it becomes difficult to write a general cost function to include differences in product quality where there are significant joint costs of production for all or some quality levels. Therefore, this model excludes product differentiation and is based on Claycamp and Massy's (1968) model.

Let

X_{mi} be the number of promotional units of type m directed at segment i;

c_{mi} be the cost per unit of promotion type m for segment i.

For simplicity, assume costs/unit of all media are constant for a given segment. Therefore, total cost of promotion of type m for segment i is:

$h_{mi} = c_{mi}\ X_{mi}$

$X_i = (X_{1i}, X_{2i}, \ldots X_{mi})$ is the column vector of promotion to segment i.

Using a strategy like the one used in the simple price model:

$q_i = f_i(p_i, X_i)\ i = 1,2,\ldots n(\text{segments})$

$c = g(Q)$

$Q = \sum_i^n q_i = \sum_i^n f_i(p_i, X_i)$

For purposes of this model, we will neglect differential costs of transportation and shipping. These are very realistic as later applications discussed in this chapter involve local markets with no differential costs (excluding promotion) between segments.

The profit function can be written thus:

$$\pi = R\text{-}C = \sum_i^n p_i f_i(p_i, X_i) = q[\sum_i^n f_i(p_i, X_k) - \sum_i^n c_i X_i]$$

In this case the last term is simply h_i, the total cost of all promotion directed at segment i. This model can be carried further to either develop an optimal price and promotion strategy with or without budget constraints. Also, costs can be allowed to vary among media. These extensions will not be explicitly treated here, however, the theory of segmentation leads us to the conclusion that a segmentation strategy can lead to optimal pricing and promotional strategies for the firm and is consistent with neoclassical economic theory.

Managerial Practice of Segmentation

Many segmentation studies have appeared in the literature. However, most of these studies have not attempted to use the results as a managerial input but rather were used as additions to market behavior "theory." This literature is reviewed extensively in Chapter II and is purely ancillary to this dissertation. The majority of published studies which were used for actual market segmentation by firms fall under the category of "product positioning" studies.

Product positioning studies typically involve procedures to find:

1. Dimensions of product characteristics and promotional appeals that are salient to consumers.

2. The relative importance of these dimensions and consumers' preferred positions (ideal points on these dimensions).

3. The distribution of preferences in the population for the existing brands.

4. The optimal position for the product and/or appeal on each dimension, taking into account the distribution of preferences and the positions of existing brands.

Benefit Segmentation

The major studies in the area of managerial practice of market segmentation in the context of product positioning are the works of Volney Stefflre (1972) and Russel Haley (1968). Stefflre's approach is essentially "brand segmentation" and is concerned with determining how consumers perceive a set of brands in a product category. The end result of this type of research is a spatial representation of the brands utilizing multidimensional scaling techniques. Haley's approach groups consumers according to benefits desired from a particular product category and has been referred to as "Benefit Segmentation." It is based primarily on cluster analysis methods and has enjoyed widespread application by marketing consultants.

Benefit Segmentation will be the primary focus of this study as it has been used by many marketing consultants who have claimed success, but who curiously have never provided empirical verification of its procedures.

An example of Benefit Segmentation. Haley (1968) provided the first published article on market segmentation based on "benefits sought." His application was to the toothpaste market where he discovered four groups or benefit segments who sought relatively different attributes of the product when making a purchase decision. The four groups were labeled the "sensory," "sociables," "worriers," and "independent" segment. The basis of separating this market into these four categories was on the principal benefits sought from the product class. The "sensory" segment name was placed on the group of people who chose a brand based on flavor and product appearance, the "sociable" lable on those who valued brightness of teeth highest, the "worriers" valued decay prevention highest, and the "independent" segment placed the most value on low price. Further analysis of these segments revealed differences in demographics and life-style. Thus advertising media targeting and product positioning was made controllable by the sponsor and not just self-selective. Also, certain brands were disproportionately favored according to how well their product characteristics and positioning matched up with the benefits sought by a particular group. Hence, the results of this type of study also include the type of results that studies like Stefflre's would yield.

Haley only provides a general idea of how his study was done. Others have provided more detailed instructions of their work, however, for the most part empirical verification is lacking (Sawyer and Arbeit, 1973; Wilkie, 1971; Mitchell, 1973; Johnson, 1972). A summary of the approaches of the above authors is represented by the chart. (See Chart #1.)

<u>STAGE 1: Segment creation</u>. The first step in creating segments is to establish a set of attributes that represent

CHART #1

STAGE I: SEGMENT CREATION

DETERMINATION OF IMPORTANCE
WEIGHTS (DIRECT OR DERIVED)

ELICITATION OF IMPORTANCE
VECTOR FOR EACH INDIVIDUAL

INDIVIDUAL ASSIGNED TO GROUPS
BASED ON SIMILARITY OF IMPORTANCE
VECTORS

STAGE II: SEGMENT TESTING

DESCRIPTION OF
MARKET STRUCTURE

ANALYSIS OF PURCHASE BEHAVIOR
DIFFERENCES BETWEEN SEGMENTS

ANALYSIS OF KEY TARGET VARIABLES
FOR PROMOTIONAL AND PRICING
DIFFERENCES

GENERATION OF
TARGET STRATEGIES

the range of attributes available from and desired in the product class in question. This list of attributes may include redundancies which are either real or only perceived as real by consumers. In practice, a wide set of attributes is used.[1]

This set is usually composed from previous attribute studies, literature on the product class, salient advertising points, executive judgment, and/or perception testing of the product class in the field.

The next step consists of eliciting an importance vector for each individual. Many ways have been proposed for doing this and, since most attitude models contain an importance vector (Howard and Sheth, 1969; Engel, Kollart, Blackwell, 1972; Fishbein, 1967; etc.), the literature contains many examples.

For the purposes of benefit segmentation alone, two major categories of measures are direct and derived measures (Green & Carmone, 1970). Direct measures consist of exercises such as constant sum evaluation of a vector of attributes or marking offfon a scale how important each attribute is to the respondent. Thus, direct measures entail the respondent's direct evaluation of each attribute based on the overall consideration of its importance in his decision to choose a brand in a particular product class. Derived mea-

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[1]Marshall Greenberg, National Analysts, Inc., Personnel Communication.

sures are a result of measuring the trade off between product attributes (Johnson, 1972) or from the distance of each attribute from an ideal (either explicit or implicit) brand (Green and Rao, 1972).

Direct measures are most often used as they entail a very simple respondent task and are less costly and less error prone than derived measures. The use of direct measures brings up the first of three basic research questions. That is, the choice of standardization procedure, if any, to be used on the data. Given a data matrix of subjects by variables, four methods of treating the data prior to analysis are standardization by row, standardization by column, factor analysis of the data, and the use of the factor scores for each individual, and raw data.

Standardization by column is a commonly used procedure when the scales of the variables differ significantly. Then the procedure of subtracting the mean and dividing by the standard deviation yields a standardized or Z score which then makes the variable comparable (Hartigan, 1975).

Standardization by row was used by Sawyer and Arbeit (1973) in order to make individuals comparable when they may have used a set of scales differently.

Factor analysis generation of factor scores was used by Wilkie (1971) to obtain a reduced set of orthogonal scores which represented the original variables. It should be noted that this procedure supersedes standardization by column since it operates on the data matrix in a similar but more complete way.

Finally, raw data is the most often used alternative as it is simpler and when the analysis is complete it is easier to relate the results back to the original questions asked of the respondents.

Therefore, as no one has evaluated these four data procedures comparatively in the benefit segmentation context, the first research question to be answered is "Which data procedure is most consistent over split halves of data and gives the most clearcut solution in benefit segmentation?"

The final step in the creation of segments is a cluster analysis of each individual's vector. Respondents are grouped based on the similarity of their importance vectors. Most researchers have used either HICLUS (Johnson, 1965) or Howard Cluster (Howard & Harris, 1966) for this step. In the context of benefit segmentation, no published studies have appeared evaluating alternative clustering approaches. Therefore, research question number two is "In the benefit segmentation context, what rules should govern the choice of clustering algorithm and how sensitive is the solution to algorithm choice?"

STAGE II: Segment testing. Segmentation testing consists of a description of the market structure. Here each segment is described by various groups of variables sequentially and finally target strategies are proposed for each segment which management wishes to reach.

First each segment is described by the unique points it has in terms of the importance vector of its members. Those attributes on which it scores high or low, usually on a crosstabulation or oneway ANOVA, identify it according to benefits sought from the product class. This step is comparable to Haley's naming a segment as worriers since decay prevention was their main concern. This analysis is further enhanced by a comparison of segments on their lifestyle and personality traits. Haley's labeling of the segment of worriers was strengthened by the relatively strong score of that segment on hypochondriasis and conservatism. Also, demographically, they tended to have large families.

Next, the purchase behavior of each segment is evaluated. In Haley's case it was an evaluation of brands favored. The assumption is that people tend to choose the brand most like their "ideal" in terms of benefits sought. This relates us back to the product positioning work of Stefflre. Each group is identified by product attributes it seeks and brands it prefers.

The next two steps are really in the hands of the manager according to the situation. Key variables are identified which make a segment (i.e., market position) unique. When introducing a new brand, the brand manager can emphasize appeals based on benefits the new brand has, but which an existing brand does not match up well with the segment that presently favors it. Or an existing brand might be repositioned or evolve a new set of appeals to better appeal to a particular segment. Each of these strategies, as well as others, depend on the strength each existing btand has in its position and the value (demand for the product) of each segment. If the demand curves of price and promotion were identifiable for each segment, a microeconomic approach would be theoretically possible; however, usually a brand for each segment must be evolved as promotion and distribution overlap make the use of multiple appeals in a single medium a chance for alienation of a segment; and different pricing of a brand when the final brand choice is self-selective rather than controlled at the retail level is impossible.

The third research question concerns itself with the stability of the market over time. Advertising and other promotional efforts by competitors as well as external forces such as consumer awareness, the FTC, the FDA, as well as a desire for variety (Reynolds, 1965) can change an individual's importance vector which is the basis for benefit segmentation. Thus, the third research question is "Is the solution stable over time?"

The implications are very important managerially. If the type of segment changes, then this portens a change in brand positions in the market. A brand must change its appeals or suffer the consequences of allowing the competition to reposition themselves either purposely or accidentally nearer the existing segments and thus nearer customer ideal points. A new segment might arise which is ill served by the existing brands, thereby creating a profitable position for an innovator. Also, segments may choose a brand more, necessitating a change in promotional effort from a policy of attracting switchers, to a policy of retaining users.

Also, more subtle things might occur. Each set of unique ideal points might remain but the individuals themselves might change groups. This may call for no action if all other key variables change in a like manner. But, if using Haley's example, worriers are now young unmarrieds and sociables have large families, the manager may have to change media policy while keeping the same appeals. All these avenues will be explored in detail using a retail banking situation to be described in Chapter III.

Summary

This chapter has defined segmentation in general, in the context of simple price theory, in the extended model which includes promotion and in the context of contemporary product positioning. Specifically, the study has zeroed in on benefit segmentation as a managerial path to product positioning and has identified procedures for benefit segmentation studies. Three research questions have been pointed out which represent weak points in the empirical validation of the benefit segmentation procedure. Briefly, they are data type with regard to consistency and usefulness of solution, choice of algorithm with regard to the same criteria, finally, and most importantly from a managerial policy perspective, the stability of the solution over time.

Chapter II outlines the methodology of other segmentation studies.

Chapter III introduces the data base and the clustering algorithms and theories, as well as minor research questions.

Chapter IV reports the most successful data type and clustering algorithm with respect to consistency and usefulness of solution.

Chapter V evaluates the solution over time and evaluates the managerial implications.

Chapter VI presents the implications of the study and relates the results back to general marketing theory and proposes a research strategy for the extended price theory model.

CHAPTER II

PAST RESEARCH ON SEGMENTATION

This chapter will review criteria for segmentation proposed by several authors and will link these criteria with the econometric type methodology representing the bulk of the literature. Next, the work done with path analysis and typologies to segment buyers will be briefly examined as to strengths and weaknesses. Brute force scaling and clustering studies will also be examined for their contributions; namely, in the area of product positioning. Finally, benefit segmentation studies will be reviewed as to their methodological strengths and weaknesses.

Criteria for Segmentation

In the last chapter the microeconomic theory of price discrimination was presented. This model strongly influenced most of the quantitative studies of market segmentation. That is, the studies attempted to define segments such that demand schedules differed with respect to price and promotion, and then to allocate resources to each segment until marginal revenue equaled marginal cost, or, until incremental returns were equal across segments, or, a budget constraint was reached. The major problem with a direct use of this strategy is segment definition. In attempting to define segments, the first step in any segmentation study, there are three criteria which must be satisfied. Several authors have provided different views on what these three criteria should be. Kotler (1967) proposes "measurability, substantiability, and accessibility." Frank (1968) suggests "identifiability, variation in demand, and variation in response to market variables." Wilkie (1971) lists "homogeneity within and heterogeneity between groups, usefulness as a correlate of behavior, and efficiency as a target for marketing tools."

To a great extent these three sets of criteria overlap. Kotler and Frank use different words to operationalize the same process on their first two criteria. Measurability and identifiability both mean the ability to measure and label characteristics of individual consumers which place them in different segments. Substantiability and variation in demand mean there is some difference in the behavior of these groups of people, which in the price theory model is the appearance of more than one demand curve. Kotler's accessibility is the ability of the marketing manager to take advantage of these differences either through pricing or promotional policy or both. Frank's "variation in response to marketing variables" is a more operational term for the same idea; namely, the tools of the manager represented as variables have different elasticities across segments.

Wilkie's criteria are similar in spirit but offer more definition in an operational sense. "Homogeneity within and heterogeneity between groups" simply says that individuals within a group (segment) should be very similar on certain variables and should be different from the individuals in other groups. This implies a necessity of not only forming groups based on individual similarities (for example, cluster analysis, regression), but also testing the differences (for example, ANOVA, discriminant analysis). Next, Wilkie offers "usefulness as a correlate of behavior." This implies that there should be some behavioral differences in patronage of a store or purchase of a particular brand between segments. Thirdly, he proposes "efficiency as a target for marketing tools" which means that the differences between segments must be described in a way which is useful in the real world of marketing. That is, one must know where the target segments are in the market in order to aim his price and/or promotion policies correctly.

In spirit, all three authors have proposed similar criteria. Wilkie's are the most easily operational and will be used in this study.

A fourth criterion is proposed here, and that is stability over time. This property concerns the longevity of a segment and its position in the market. There is nothing to suggest that there are enduring characteristics in any market with respect to any of the above three criteria; therefore, it is useful for the researcher and manager to note changes in segments, positions of segments in a market, changes in demand of those segments or any other characteristic of a market which changes over time.

Studies Utilizing Econometric Methodology

In practice, most researchers in market segmentation have generally used some aspect of observed purchase rate to represent the demand curve for a household and has attempted to relate the purchase rate to variables which represent characteristics of the households. Typically, the relationship between the descriptive variables and the purchase rate has been analyzed by the use of multiple regression. The model attempts to predict purchase behavior (dependent variable) using household characteristics (independent variables).

Four general bases of observed purchase behavior have been used in this type of research:

1. Average purchase rate
2. Heavy half usage
3. Brand loyalty of brand choice
4. Private brand proneness

These four general bases of observed purchase behavior have been studied with respect to three types of segmentation variables:

1. Demographic and socioeconomic (SES) household descriptors.

2. Personality and lifestyle (AIO's) descriptors of individuals.

3. Media habit of households and individual members.

Typically, R^2 (proportion of variance in the dependent variable explained by the independent variables) is the criterion used to evaluate these models.

Average purchase rate. Frank, Massy, and Boyd (1967) examined the relationship of average purchase rate and 14 demographic and SES characteristics in an extensive and quite broad study of 57 different product categories which covered 491 households. The proportion of variance in purchasing explained by these 14 characteristics was very low. Rice cereals has a R^2 of .29, 46 of the 57 products had R^2 less than .2 and the average R^2 was .11.

Three studies using a different sample added personality traits to the demographic and SES descriptors. The hypothesis was that these additional variables would provide more useful predictions of purchase behavior (average purchase rate). Scores on 15 personality traits based on the Edwards personal preference schedule were obtained and added to the regression equation. Koponen (1960) in an analysis of two product classes, obtained R^2 of .13 and .06. Later, a study by the Advertising Research Foundation investigated purchases of 3206 households with respect to one and two-ply toilet tissue. Their study was sunk with R^2 of .12 for one-ply and .06 for two-ply tissue (Hildegard and Krueger, 1964). Massy, Frank, and Lodahl (1968) again used demographic. SES, and personality descriptors in the study of coffee, tea, and beer purchases and found R^2 of .07, .07, and .07.

Frank, Douglas, and Polli (1968) studied the relationship of brand loyalty to 14 demographic and SES descriptors for 44 of the 57 product classes in the first study mentioned and obtained an average R^2 of only .12. The Massy, Frank, and Lodahl (1968) study on beer, tea, and coffee reported the relationship between brand loyalty and demographic, SES, and personality variables with R^2 of .10, .07, and .05. Hildegaard and Krueger's study (1964) when using brand loyalty as the dependent variable reported an R^2 of .05 for one-ply and .07 for two-ply tissue. Farley (1963) studied loyalty as a function of two demographics and total quantity purchased for 17 product classes. Eleven of the seventeen equations had R^2's of less than .04.

Another interesting part of the literature on using demographics, SES, and personality measures as a basis for segmentation is the series of articles written by Franklin Evans and critics on the differences between Ford and Chevrolet owners (Evans, 1959; Steiner, 1961; Winick, 1961; Evans, 1961; Westfall, 1962; Kuehn, 1963; Evans & Roberts, 1963). Once again demographics, SES, and personality measures didn't seem to be a useful base for segmentation.

A study of loyalty to private brands or "private brand proneness" done by Frank and Boyd (1965) reached an average R^2 of .18 when using in store variables, but only using demographics and SES yielded an R^2 of .04. Burger and Schott (1972) used discriminant analysis to study private brand buyers and found demographics and amount of product use to be unimportant, but determined that attitude toward the selling store, and price promotion were most useful in identifying this segment.

The conclusion that demographics, SES, and personality descriptors have not accomplished the task of uncovering meaningful segmentation correlates is well founded. Frank (1969) argues that the design of segmentation studies should be improved in the specification of both dependent and independent variables. Bass, Tigert, and Lonsdale (1968) argued that strategy can be improved even though R^2 is low because significant differences exist in group means. Massy (1970) replied that returns on such a strategy are dependent on R^2 and thus can be inferred to be low when R^2 is low. In the same article Massy evaluated a strategy including the costs of formulating and carrying out the research, and it was not clear that the incremental gain was positive.

Some have attributed the low R^2 to the possible bias introduced when not using a truly continuous variable as the dependent variable. Morrison (1972) demonstrated that this influences R^2 very little and one should look elsewhere for the solution.

Heavy half usage. Twedt (1964) has answered critics of the low R^2 by suggesting that a simplification of the dependent variable to a dichotomous one representing heavy and light users can be applied. This is based on the knowledge that in most product classes the fifty percent of the users which purchase the product most often account for over 80 percent of the purchases. Thus, Twedt reasoned, it is most profitable to match the "heavy half" profiles to media habits. Bass, Pessimier, and Tigert (1969) found good results in utilizing this approach. Several media tabulating services (such as, Target Group Index) report cross-referenced data on product use and use of different media vehicles by consumers thus simplifying the task for marketing managers and media schedulers.

AID Studies

There is a further group of studies which attempt to relate average purchase rate to various groups of demographics, SES, and personality variables. However, rather than using regression analysis with R^2 as a criterion of success, AID (Automatic Interaction Detection) was used. AID allows the analysis to be carried out without assumptions of linearity, absence of interaction, and normality yet measures the effects of up to fifty variables on a dependent variable.

(Sonquist and Morgan, 1971). Some marketing studies have used AID with dependent variables representing post purchase dissatisfaction and other factors which do not really lead to a generalized segmentation of the market based on demand for the product, but instead represent rather a searching for hypotheses for specific behavioral processes. A few AID studies have used average purchase rate as a surrogate for the demand curve thereby providing a basis for segmentation stragegy.

The most representative study of this type was done by Wilkie (1971). Wilkie's study is interesting since it attempts to relate demographics, SES, lifestyle, personality, attitudes toward product class, brand preferences, perceived use opportunities, and differential benefits sought to purchases of the product. So simply, Wilkie evaluated most of the variables which could possibly explain the differences between purchase rates.

Wilkie (1971) pointed out some shortcomings of the AID approach. First, because AID searches for the best predictor at each stage process it is susceptible to spurious errors due to errors in the data itself. Ordinary regression has the same type of problem when a validation sample is not used. However, regression takes the interdependence of the independent variables into account and yields the net effect of all variables used in the model. Second, AID may select only some of the variables and count their gross effects on the dependent variable. Third, AID results are usually represented by a tree diagram which is subject to spurious interpretations as to the effect of each variable on the dependent variable or overall analysis. Fourth, Sonquist and Morgan (1971) suggest very large sample sizes should be used, and consistency should be checked by means of split half samples, a procedure missing from marketing studies utilizing this methodology.

Wilkie's (1971) overall results were very disappointing; meaningful segments were not found. He concluded that conclusions from past research were substantial in that no strong support could be found to meaningfully segment buyers.

Typologies

Typologies are classification schemes used to identify homogeneous subsets of buyers from a generally heterogeneous set of buyers. There are many ways to classify buyers although two major approaches can be identified. One method is to postulate variables or qualities, based on overall theory, which are relevant to the classification. This type of endeavor is exemplified by the studies in previous sections of this chapter concerned with econometric type studies. Proceeding from the microeconomic theory of segmentation, researchers attempted to identify variables which exhibited a pattern or correlation yielding meaningful discriminators of differential market demand. As was observed, the empirical studies failed to support the theoretical postulates. However, econometric segmentation studies are often thought of as scientific as they proceed from theory through hypothesis, testing, and conclusion.

Another approach is to collect observations of a variety of variables on the phenomena to be studied. Through computational procedures, different dimensions are identified. Then subjects (or objects) are classified into different groups based on differential measures on each of the dimensions.

Several notable examples of classification have appeared in the market segmentation literature. Myers and Nicosia (1968) used measures of nine supermarket attributes obtained from 200 female respondents in a 15 week panel. Nine "clusters" or groups of shoppers were uncovered in their analysis, although the ninth group consisted of one unique individual. Myers and Nicosia went on to show the sensitivity of the solution to the factor analysis procedure used on the original variables to derive dimensions on which to compare the individuals. This was the first major study of this method of discovering consumer groups and although it presented no substantive results in terms of segmentation theory or consumer behavior, it set the methodology for many attempts by subsequent authors.

In their review article, Green and Frank (1968), uncovered only three attempts to use numerical taxonomy or "cluster analysis" prior to Myers and Nicosia (1968) study, none really segmenting buyers. Following the articles by Green and Frank (1968) and Myers and Nicosia (1968), many studies appeared which used cluster analysis. Many of these were what can be called dredging attempts in so far as almost every possible variable was put into the analysis. The resulting typologies, if successful computationally, were useless or trivial in a managerial sense. The results often looked impressive when represented by a three dimensional figure or graph, but usually lacked any real insights which could be the basis of promotional strategy.

A further major problem with most of the studies done using cluster analysis was the absence of any consideration of market dynamics. No tests of stability of the solution over time were attempted.

<u>Dynamic typologies</u>. Two recent major studies have addressed the problem of market dynamics within a segmentation framework. These studies are notable since any managerial policy must take market dynamics into account or suffer the possible consequences of implementing an obsolete strategy.

The major segmentation work related to longitudinal behavioral theory is the study by Monroe and Guiltinan (1975) of store choice in a retail grocery market. The authors modelled the sequence of effects of store choice behavior and developed the use of time-path analysis to draw conclusions about the probable direction of influence between general opinions and activities, store perceptions, specific planning and budgeting strategies, and attribute importance. Although the major focus of the study was on shoppers' information processing, substantive managerial implications could be drawn from the results in a longitudinal context about retail store choice to show the viability of the methodology to identify buyer typologies.

Blattberg and Sen (1974) after an exhaustive review of the literature, proposed a new type of segmentation based on multidimensional purchase behavior. Their strategy was based on a three step research procedure. The first stage developed several dimensions of each consumer's purchase behavior such as brand loyalty patterns, store loyalty patterns, deal proneness and size patterns. The second step classified individuals into groups based on common sequences identified in stage one. Classification revealed segment size and a discriminant procedure was used to group the consumers in terms of the available sequences. The third stage was segment identification. This stage attempted to differentiate the segments based on demographics and attitudinal variables.

Blattberg and Sen (1974) used the purchase sequences of 50 consumers who had a record of 31 or more purchases of aluminum foil. The segments were defined by visual analysis of each consumer's purchase history using data on brand, store, package size, and price. Eight segments were defined in this way such as "high price brand loyal," "national brand loyal," "deal oriented," and so on. A Bayesian discriminant procedure was used to classify the consumers into segments based on a model which represented their string of 31 or more purchases. The discriminant analysis revealed that 85 percent of the customers were correctly classified into segments. In the last stage the authors proposed the use of an N-way discriminant analysis to identify demographics and attitudinal variables which could aid in media strategy; however, they did not illustrate its use in terms of their example.

Monroe and Guiltinan's study and Blattberg and Sen's article significantly advance the thinking on segmentation strategy. Both studies illustrate the usefulness of evaluating marketing studies over time. Thus, an important consideration in segmentation strategy is the ability of any research analysis to handle longitudinal considerations.

Benefit Segmentation Revisited

Benefit segmentation offers the best managerial input in a segmentation framework since it is prescriptive as to product and brand appeals, and contains steps for revealing brands preferred (or stores favored), media habits, demographic strengths of segments and lifestyle profiles of segments. As referenced in Chapter I, Haley (1968) was the first to use the term to describe the process of segmenting a market based on benefits sought. Haley's philosophy as well as the writings of later researchers have outlined the steps of benefit segmentation research as appear in Chapter I (Sawyer & Arbeit, 1973; Wilkie, 1971; Mitchell, 1973).

Methodologically, several steps can be improved or empirically validated as suggested in other studies. Specifically, Myers and Nicosia (1968) studied the sensitivity of their typologies to changes in the treatment of the input data. Given a matrix of subjects by variables, they analyzed the sensitivity of the solution by normalizing the variables (columns) and doing a factor analysis. Frank and Green (1968) suggest using factor scores also. Wilkie (1971) and Mitchell (1973) both used factor scores in their benefit segmentation studies as the data input to cluster analysis. Sawyer and Arbeit (1973) standardized by rows, that is, each subject's scores were standardized, prior to cluster analysis. Thus, the literature does not resolve the question: "Which data procedure is most consistent and gives the clearest solution in benefit segmentation analysis?" As stated in Chapter I, this is the first research question.

In the same vein of sensitivity of result, no one has evaluated alternative clustering algorithms. Wilkie (1971) used Johnson's (1967) clustering scheme, while Sawyer and Arbeit (1973) and Mitchell (1973) used Howard Harris (1966) cluster analysis. (Both methods are explained in Chapter III.) Thus, the second research question is "In the benefit segmentation context, what rules should govern the choice of clustering algorithm and how sensitive is the solution to algorithm choice?"

The third contribution in the literature is the evaluation over time. No one has evaluated benefit segmentation results over time. Thus, the third question this study is concerned with is "Is the solution stable over time?"

Direction of This Study

This chapter has presented highlights of the segmentation literature to show the diversity of approaches and what each approach has to offer in general. Using benefit segmentation as a starting point, and taking insights such as longitudinal evaluation from other studies, a more exhaustive benefit segmentation methodology will be evaluated. The rest of the study will be concerned with evaluating benefit segmentation in a retail bank context. Panel data will be introduced in the next chapter which will be used to answer the three proposed research questions. Chapters IV and V will present the analysis of the questions, and Chapter VI will state the conclusions and summary.

CHAPTER III

PLAN OF THE ANALYSIS

Introduction

The major concern of this study is an evaluation of the procedures used in benefit segmentation. Three major research questions have been proposed dealing with type of data input to cluster analysis, clustering algorithm choice, and the stability of clusters over time.

This chapter introduces the data base for the empirical analysis and managerial setting and reviews studies using cluster analysis benefit segmentation studies. Finally, the major and minor research questions are operationalized, and the algorithms and evaluative methodology are presented.

The Data Base

The data base describes consumer behaviors and attitudes in a large midwestern city. The point of emphasis is on the retail banking market in that city which contains six major banks. The economic environment is relatively closed as this city is lake locked by an international border and is separated from the nearest major city by fifty miles. From these facts as well as patronage habits data, one may assume that virtually all banking in this city is confined, at the nonindustrial level, to the six banks represented in this study. Three of the banks are savings banks and three are commercial banks.

Data Collection Procedures

During two time periods, households were measured regarding their attitudes on seventeen dimensions toward the six banks, the importance of seventeen different benefits associated with banks, general and banking lifestyles (AIO's), banking habits (patronage of various available services), and demographics. The variables available for analysis are listed in Table 1. The two waves were collected in 1972 and 1974. The exits and entrants to the sample frame were eliminated from the panel design after no bias was revealed demographically, and the 345 subjects who participated in both surveys comprise the panel. The data was made available by two sponsoring banks who must remain nameless.

This will be the primary data base and all details, implications, and results reported are based on it. A split-half design will be used throughout to provide a check for consistency.

Previous Benefit Segmentation Studies

Three major benefit segmentation studies have appeared in the literature which have presented the methodology used: Sawyer and Arbeit (1973), Wilkie (1971), and Mitchell (1973).

Sawyer and Arbeit (1973) studied retail bank market segmentation using an importance vector of seven bank attri-

TABLE 3.1

Variables Available From Panel For Data Base 1

<u>Demographics & SES</u>

1. Home Ownership
2. Education
3. Occupation
4. Age
5. Spouse Education
6. Spouse Occupation
7. Family Size
8. Ethnic Background
9. Religion
10. Income
11. Mobility
12. Number of cars owned

<u>General Psychological Descriptors (AIOs)(123 scales) (major factors)</u>

1. Impulsiveness
2. Sociability
3. Acceptance of Innovations
4. Leadership
5. Perceived Time Pressure
6. Self-Image
7. Economy Consciousness
8. Risk Taking

<u>Psychological Descriptors with regard to Tanking (Bank AIOs)(95 scales)(major factors)</u>

1. Money Management
2. Innovations
3. Credit Card Use
4. Interest Rate Attention
5. Bill Payment
6. Checking Account Usage
7. Advertising
8. Ease of Making Financial Decisions
9. Loans
10. Favorableness of Image of Financial Institutions

TABLE 3.1 (continued)

Benefits Sought

1. Encourage financial responsibility
2. Quick service
3. Large
4. Friendly atmosphere
5. Good reputation in your community
6. High interest on savings
7. Loans are readily available
8. Convenience banking hours
9. A bank for most everyone
10. Concerned about the local community
11. Branches are conveniently located
12. Low interest rates on loans
13. Modern
14. Wide variety of service
15. Pleasant offices
16. Good advertising
17. Plenty of parking

Ratings of Six Major Banks

(Same scales as Benefits Sought; some reversed to eliminate "yea-saying")

Banking Practices

1. Ranking of Six Banks overall
2. Use of financial services
3. Banks recommended
4. Accounts held at each of the Six Banks
5. Size of accounts

Media Habits

1. Television viewing habits
2. Magazine readership habits
3. Radio Listening habits
4. Perceptions of which banks advertise most and in which media.

butes. They standardized the scales across variables to eliminate high and low column scorers from appearing different. This approach tends to make persons who score all attributes as very important, all of medium importance, or all of unimportance appear the same by giving them a set of scores near zero. Whereas the individual who discriminated between attributes would receive high positive scores on those variables marked as important and, those marked unimportant would receive negative scores. This procedure seems irrelevant since all the variables were originally measured on six point scales and since the cluster analysis looks at the data by individuals this standardization procedure should not affect the results.

After the vectors were standardized for each respondent, the vectors were submitted to the Howard-Harris (1966) cluster program and two segment through 10 segment solutions were computed. After a complete crosstabulation of segment number with each original variable, a six segment solution was chosen based on fineness of discrimination between groups and meaningfulness of solution.

Not only were the groups distinct from one another on benefits sought but also differed as to financial practices, demographic characteristics and lifestyles. A scheme was devised for the principal bank in the study to evaluate the segments for opportunities for penetration based on susceptibility or estimated potential for penetration and the cost benefit of penetration into various segments.

The research base in this dissertation is based partially on the original data in the Sawyer and Arbeit (1973) study but extends it to a second wave thus enabling a check for stability over time. Also, this dissertation will use a split half design as a validity check.

Wilkie (1971) empirically derived benefit segments using a more complicated procedure. Previous to Wilkie's study, there were no published reports of benefit segmentation procedures. Wilkie had 13 product characteristics which respondents indicated "matters a great deal," "matters somewhat," or "matters very little" in a pretest. A factor analysis was performed and six of the characteristics which were judged redundant were dropped and the seven remaining variables were used in the final study. After the data was collected, a factor analysis was again performed and four major factors accounting for 80 percent of the variance were isolated. Four variables appeared relatively independent and in order to "keep a handle" on the analysis it was decided to use those four variables rather than factor scores. Later evaluation revealed little information loss due to this choice.

Wilkie (1971) obtained his from a previous survey and developed an elaborate procedure to quantify the terms "matters a great deal," "matters somewhat," and "matters very little." The details of the scaling study will be omitted here; suffice it to say it was elaborate but of dubious value as the original data was obtained from female housewives and the scaling data from female graduate students (mostly Ph.D's).

Wilkie used HICLUS, or "Johnson Cluster" written by Stephen Johnson (1967) to group his individuals. His version was limited to 100 cases so he selected a random sample of 100 to represent his 432 available cases (a holdout sample was not used for validation). Product moment correlations (Pearson r's) were computed for the 100 subjects and inputted to the program. Output of the maximum, "diameter" method[1] was more meaningful given the fact that correlations are similarity measures.

The HICLUS output contained 18 possible cluster solutions many of which were trivial or useless, i.e., everyone in one or two groups, clusters with one member, or 28 clusters. The clustering scheme with 6 groups was picked because of group sizes, interprebility, and reasonably high homogeneity within groups.

Analysis of the six groups revealed very straightforward differences between groups and the 332 remaining cases were assigned to groups without difficulty using high and low scores on factors that discriminated strongly.

Wilkie (1971) went on to analyze differences in purchase

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[1] Details of cluster algorithms appear later in this chapter.

behavior, demographics, SES, and lifestyles. Some of the clusters exhibited tendencies toward purchase of a particular brand but overall the results were weak.

Wilkie (1971) continued to analyze the data and came up with good copy appeal and media strategy (based on demographics) but found mixed results for various "new brand trying" questions and other preference indicators. The results of the study seemed managerially useful for promotional strategy but are very erratic when one attempts to fit them to a theory of behavior. Thus, as expected, the seemingly confusing results reported are very useful in a managerial sense but virtually useless in a theory testing endeavor.

Mitchell (1973) studied the relationship between benefit segmentation, multidimensional scaling, and brand choice behavior within an expectancy theory framework. Here we will only concern ourselves with the segmentation procedure and methodology.

Information about consumers' perceptions of oil companies were gathered on a combination of factors; the firm's service stations, products, and corporate image. In-home interviews were conducted with the family member who purchased the most gasoline in fifty randomly selected households in a large metropolitan area. Twenty-six attributes were evaluated on a scale of importance ranging from "not important at all" to "very important." To segment the respondents into benefit segments, the important scales were first factor analyzed to eliminate scales which were redundant or measuring the same underlying dimensions, following a recommendation by Morrison (1967). Mitchell used a factor analysis solution that contained 14 factors (seven with eigenvalues greater than one) which explained ninety percent of the variance. The factor scores computed after a varimax rotation were used as an input to the Howard-Harris (1966) clustering algorithm.

Mitchell examined the first ten levels of clustering. Over ten levels of clustering explained less than 50 percent of the total sum of squares as within group sum of squares. Also, there did not appear to be any level of clustering where within group sum of squares dropped considerably, so the level of clustering was selected on the basis of interpretability and size of the resulting clusters. Based on those criteria, a four group solution was chosen. Mitchell went on to evaluate the relationship between purchase behavior and segment membership and found a relationship which indicated that the choice of service station was not random but related to segment membership.

The three studies evaluated provide a methodological framework for benefit segmentation studies but leave many questions unanswered in terms of validation.

Wilkie (1971) and Mitchell (1973) both used factor analysis but did not use a hold out sample or split half design to check for consistency of the factors derived. Both studies as well as Sawyer and Arbeit's (1973) used cluster analysis and all once again did not use a hold out or split-half design for a consistency check. Both types of methodology are especially appropriate for a split half design due to the absence of significant tests for the final number of factors extracted (factor analysis) or final number of groups (cluster analysis).

The Choice of Data Input

Wilkie and Mitchell both used a factor analysis as a pre-processor of the data matrix prior to cluster analysis. This is done mainly to remove highly redundant or intercorrelated variables from the analysis. Morrison (1967) points out that this should be standard procedure as redundant variables result in much "double counting" in the distance computation in most cluster algorithms. Sawyer and Arbeit used standardization by rows and as previously mentioned, attempted to avoid certain response pattern problems by doing so.

Mitchell (1973) and Sawyer and Arbeit (1971) both used Howard-Harris (1966) clustering while Wilkie (1971) used HICLUS or Johnson (1967) clustering. Both clustering algorithsm plus a third one are described in a later section.

Green and Rao (1969) did an analysis of ten different forms of proximity measure input to the Johnson clustering algorithm and concluded that the output is extremely sensitive to the <u>form</u> of the proximity measure (based on the same data, of course) used as input to the Johnson clustering algorithm. In another study, simple Pearson r's arranged as a similarity matrix gave results highly consistent with several other measures, and reproducible over split halves (Green and Rao, 1972).

The first question to be researched is the choice of data input to the Howard-Harris algorithm. As it has not been resolved in the literature, especially in a segmentation framework, it will be evaluated here. Four data types will be submitted to the Howard-Harris algorithm and evaluated for consistency of output over split halves, contribution to later analysis, and usefulness in understanding final solution.

The four data inputs are raw data, standardization by row, standardization by column, and factor scores. The original data matrix consists of a 345 x 17 matrix composed of the 345 subjects' 17 item vector of importance scores of the bank attributes previously described in Table 1. In the split half analysis, the 345 subjects were randomly assigned to two groups (one subject being randomly dropped to facilitate statistical analysis). Four matrices are constructed for each split half as follows. Raw data consists of the original data, standardized by row consists of a 172 x 17 matrix of Z scores[2] computed for each subject across variables, standardized by column is a 172 x 17 matrix of Z scores computed for each variable (column) across subjects. Factor scores are a (172 x K) matrix where K is the number of factors representing the underlying dimensions in the data. Factor scores are computed by multiplying the raw data matrix by a coefficient matrix representing the underlying dimensions. Thus, in a simple sense the factor scores of an individual represent a weighted set of summed scores for that individual on the underlying dimensions. See Anderson (1958) and the Statistical Package for the Social Sciences (Nie, et. al., 1975) for a fuller explanation.

Tests of consistency are an evaluation of chi-square (X^2) computed on group sizes across split halves at each level of clustering and simple correlation coefficient computed on the vector of raw scores for similar groups across split halves.

Unless a greater consistency of results is apparent, standardization by row and standardization by column will be rejected for the following reasons. Standardization by row scores do not handle redundancies across people. Standardization by

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[2]For example, a row Z score is $Z_{ij} = \dfrac{R_{ij} - \dfrac{\left(\sum_{j=1}^{17} R_{ij}\right)}{17}}{\sigma_i}$ where σ_i is the row standard deviation.

column in scope of the analysis is dubious since the raw data is based on standard six point importance scales originally. Both forms of data also confuse the ensuing managerial interpretation. Factor analysis, a priori, seems to be the leading contender as it removes redundancies, and allows F-Tests using the raw data on the cluster results without violating the statistical assumptions of the F-Test (Morrison, 1967; Green, Frank, and Robinson, 1967).

The Choice of Clustering Algorithm

As previously mentioned, two different clustering algorithms have been used by researchers in benefit segmentation studies. In this study a third algorithm will be evaluated known as TAXMAP (Carmichal, 1974). The three algorithms are described below.

The Three Clustering Algorithms

JOHNSON HIERARCHICAL CLUSTERING: Johnson (1967) performs cluster analysis on a hierarchical basis using as input a dissimilarity matrix. In this study, a similarity matrix was used and converted to dissimilarities.

Theoretical discussion. Let dij be a measure of dissimilarity between the pair of objects i and j. Johnson (1967) shows that if the data are "perfect" (no missing data, no ties), the dissimilarity measures obey the ultrametric inequality, namely $\delta(x,z) = \max(\delta(x,y),\delta(y,z))$. The problem can be reduced to finding a set of real numbers $(a_o, a, \ldots a_m)$ associated with m+1 clusterings $(C_c \ldots c_m)$ such that

$$0 = a_o, a, \ldots . a_m$$

$$C_k - i = C_k (K = i \ldots . m)$$

and the set of numbers obey the ultrametric inequality. Johnson (1967) proves the existence of a hierarchical clustering scheme for every matrix of dissimilarity measures. In the algorithm, two functions are used; namely, MIN (connectedness) and MAX (diameter). The methods can be described as follows:

1. Cluster c_o with value 0 to represent the trivial clustering where every object is its own cluster.

2. Assuming we are given the clustering C_{j-1} with the dissimilarity function defined for all objects or clusters C_{j-1}, let a_j be the smallest nonzero in the matrix. Merge all pairs of points and/or clusters with distance a_j to create c_j of value a_j.

3. Create a new similarity function for c_j - if x and y are in c_j and not c_{j-1}, d(x,y) to z is defined y:

$$d((x,y),z) = MIN(d(x,a),d(y,z))$$

4. Thus, a new dissimilarity function is found.

The MAX method is the same as the MIN method except in step 3:

$$d((x,y),z) = MAX(d(x,z),d(y,z))$$

HOWARD-HARRIS CLUSTERING: This routine forms groups of objects using an objects by variables matrix. The algorithm uses the criterion of minimum within-group variance at each level of clustering. In the examples in this study, the individual respondents are the objects to be clustered.

Theoretical discussion. Given n objects (persons) $x_i = x_1, x_2, \ldots, x_n$ where each x_i is an N dimension vector where N is the number of variables defining each x_i. Let P(S,p) represent a p - fold portioning of the set S, into subsets s_1 s_2, etc.

Hierarchical clustering can thus be stated:

Given $(x_1, x_2, \ldots, x_n | x_1 \varepsilon S)$, each categorized by a number of variable (N), partition S into subsets internally homogeneous and as mutually dissimilar as possible. Dissimilarity of x_i and x_j can be defined as $|x_i - x_j|^2 = \sum_{K=1}^{N} (X_{ik} - X_{jk})^2$ for a set n_1 members in a group s_1. It can be shown that the sum of squared interpoint distances is comparable to the sum of squared interobject deviations from the mean of the group. This is stated thus:

$$\sum_{(x \varepsilon S_1)}^{ns_1} |x_i - \overline{x}_{S_1}|^2 = \frac{1}{2ns_1} \sum_{(x_j, x_j \varepsilon S_1}^{NS_1} \sum^{NS_1} |x_i - x_j|^2$$

where $\overline{x}_{S_1}$ is the group centroid of S_1.

The total variance of all $N \varepsilon S$ is:

$$V_T = \frac{1}{2n} \sum_{i=1} \sum_{j=1} |x_i - x_j|^2$$

For any p-fold partition $V_T = V_B + V_W$

$$V_w = {}_{S_1 \varepsilon P(S,p)} V_{S_1}$$

The practical problem is thus:

Find P(S,p) so V_w is minimized.

Computational routine. Given a p-fold to find a p+1 fold

1. Choose a group S_1 on basis of max. V_w

2. Choose maximum variance component of $X_i \varepsilon S_1$

3. Split at mean value of maximum variance component of $X_i \varepsilon S_1$.

4. Compare distance from each $X_i \varepsilon S$ to centroid of each of the p+1 groups. Shift points until group positions are represented by minimum squared distance to centroid of each cluster.

THE TAXMAP CLASSIFICATION MODEL:[3] The TAXMAP algorithm performs a series of statistical evaluations of the relations among a set of Operational Taxonomic Units (OTU's) described by a number of variables (attributes).

Theoretical discussion.

Assumptions about the validity of attributes for classification

Existence and homology of attributes

The basic assumption is that the individuality of an

[3] Shifted and adapted from a mimeo writeup by J.W. Carmichael, Dept. of Bacteriology, University of Alberta, Edmonton, CANADA (1974).

OTU can be divided into aspects or parts, and that different OTU's can be divided into parts in the same way. That is, that there is a one-to-one correspondence between the selected attributes for any pair of OTU's. This assumption is based on the assumption that there is some underlying set of causes or restrictions which gives the OTU's comparable aspects. In biology, the application of these assumptions is referred to as the problem of homology. It can be taken as axiomatic that: the more disparate the OTU's, the fewer aspects they will have that we can be reasonably sure are homologous.

Validity of attributes in relation to the purpose of classification

If the purpose of a classification is to be generally descriptive and predictive, homologies should be based on the underlying causes that influenced the generation of the OTU's. The attributes chosen should be a representative sample of all such attributes, (of which there may be an infinity). The only test for achievement of a representative sample is the convergence of classifications based on different samples of attributes. If convergence occurs, we will have achieved our first purpose, whether or not our samples of attributes are actually representative in terms of underlying causes.

If the purpose of a classification is more restricted and explicit, then we can use that purpose as an overlying definition of causality and the choise of attributes and the determination of homology become less difficult.

Assumptions about relative proximity. The relative difference (d_{ij}) between the states (V) of the i^{th} and j^{th} OTU's on a single attribute is taken to be quantified by

$$d_{kj} = |V_i - V_j| / (V_{max} - V_{min})$$

In other words it is the difference between the observed values divided by the observed range over all the OTU's. For efficiency in computation, the computer program first subtracts V_{min} from all of the observed attribute values and then divides them vy ($V_{max}-V_{min}$) before computing the d's between all of the pairs of OTU's.

The relative difference (D_{ij} between the i^{th} and j^{th} OTU's based on a number of attributes is taken to be weighted (w) arithmetic average of their relative distances on each attribute. For n attributes

$$D_{ij} = \Sigma[(d_{ij})_k \cdot W_k]/\Sigma W_k, \ k=1 \text{ to } n$$

The program provides either for weighting all attributes equally, or for weighting them according to their relative information content.

Clusters. If the OTU's are envisioned as ordered in a hyperspace defined by taking each attribute as an orthogonal axis, it is assumed that the classification desired is a partition of the OTU's into clusters whose members form a continuous, relatively dense population, which is separated from other OTU's by a completely surrounding relatively empty space. The program defined relatively dense and relatively empty by the folloiwng empirically developed procedure. The proximities between the pairs of OTU's are rank-ordered, the closest first. A five percent "tail" is deleted from the top and the bottom of the rank-ordered list. The range of the remaining distances is determined and divided by 10 to yield a distance called CUT. This distance is added to the smallest distance in truncated list to yield a distance called QUIT. Pairs of points closer than QUIT, if they are closest pair neither of which is already allotted to a cluster, are considered to form the nucleus of a cluster. The closest point to any already in the cluster is then added to the cluster unless its distance from the closest OTU is greater than QUIT and its distance minus the average of the best and worst of such previous distances is greater than CUT, or its average distance from all the previously admitted points is greater than QUIT and the average for this point minus the average for the last previously admitted point is greater than CUT, of a ratio criterion, which prevents scattered points from bridging large, elongated clusters, is not met, or the closest point is already a member of a previously formed cluster. (See Charmichael, George, and Julius, 1968, for further explanation.)

If the closest point is not admitted, then all the members of that cluster are assumed to have been found and included. OTU's which are diffuse clusters by the above criteria, are considered to be single member clusters.

According to the assumptions of the algorithm, we are not concerned with intercorrelations of variables only redundancies. Therefore, no data comparisons will be done with this algorithm.

Guidelines to Govern Algorithm Evaluation

Six guidelines or "rules-of-thumb" will be used to govern algorithm choice. The first will be F-ratios, one for each attribute. The significance of these ratios will not be a primary indicator of a good discriminator, especially if raw data was originally used as the cluster input as this would violate the statistical assumption that the items in an ANOVA were not originally classified by those items (Green, Frank, and Robinson, 1967; Morrison, 1967). R.M. Johnson (1972), however, found that F-ratios do sharply discriminate between cluster solutions derived from real and random data.

The second guideline willbbe reproducibility. The data will be split into random halves and clustered separately. To evaluate the similarity of the result, the correlation across attribute means between each cluster from the first half and each cluster from the second half will be examined.

If two cluster half solutions are similar, they should have high correlations between groups from the two halves. This can be simply represented by a high average correlation between matched pairs of clusters. This is one of the same analyses which will be done to choose data input to the Howard-Harris algorithm.

The third guideline will be the chi-square statistic (X^2) which will indicate the extent that each split-half has equivalent sized groups. The lower the chi-square statistic, the more similar the solutions. This same analysis will also be done with the data input question.

Segmentation theory suggests that clustering techniques should be hierarchical and agglomerative (Peterson, 1974). This suggestion is not clearly evident in the case of hierarchical methods, but is desirable managerially in the case of agglomerative methods. Claycamp and Massy (1968) propose that segmentation is a grouping into distinct segments of individual consumers, hence an agglomerative method which builds up groups from individual units is preferred to a divisive method which starts with all data and partitions them into subgroups. The claim that hierarchical methods result in a better structure for market segmentation purposes is perhaps fallacious since it is not apparent theoretically. Nor has it been shown empirically that when either partitioning or joining, the best solution on one level of clustering forms the basis for the best solution at the next level

(Hartigan, 1975; R.M. Johnson, 1972). The final criterion is whether the method is monothetic or polythetic. Monothetic methods form groups based on "either/or" criterion, whereas polythetic techniques are based on considerations of overall similarity. A monothetic approach produces purer groups but as the number of attributes describing the individuals increases, it becomes more difficult to match all individuals; thus a very large group of unclassified individuals might remain. This last problem--monothetic vs. polythetic may be crucial. The managerial usefulness of a monothetic structure appears dubious as evidenced by Lessign and Tollefson's (1971) study which had fifty two groups consisting of 1 or 2 individuals of no particular managerial significance.

Howard-Harris is polythetic and TAXMAP is monothetic. A polythetic approach is more practical and will be chosen over a monothetic one given the next two considerations hold. They are the satisfactory indication of a stopping level for the clustering process for Howard-Harris or Johnson (TAXMAP as a monothetic technique has stopping rules built in) and the managerial usefulness of the solution.

The two polythetic methods will be examined by the F-ratios of the original raw data vectors of each group at each level of clustering (previously calculated). A significant drop in within group sum of squares could indicate a stopping point for evaluation (Mitchell, 1973; Calantone, 1975). Also, as suggested by Rand (1971) any level where two or more methods yield a similar solution could be the "natural" clustering level.

Finally, managerial usefulness of the solution will be used if all the other rules fail to discriminate a "good" from a "poor" clustering solution. Tryon and Bailey (1971) state that a good intuitive solution that works should be preferrable to a neat mathematic one that does not work. Thus, if all else fails, the solution that is managerially useful is the one that will be chosen.

After a solution is chosen, the market segments will be described and a managerial strategy proposed.

Stability of the Solution Over Time

The analysis chosen will be repeated with the 1974 data and the solution described. The classification of individuals in the two time periods will be compared to see if the same type of segments are uncovered and whether the same individuals occupy the same segments they did previously. This question of stability has several implications managerially in the benefit segmentation framework. The analysis will be described and the implications of the outcome will be presented.

Repeat Analysis--Are Benefit Segments Enduring Market Positions?

Using the 1974 data wave, the benefit segment analysis will be repeated. The methodology chosen from the 1972 analysis will be used and all the tests of consistency will remain. The market will be analyzed using the familiar steps of using the importance vector of the individual consumers as input to the cluster analysis. The resulting groups will be evaluated as to benefits sought and retail bank outlets favored. The benefit(s) sought by each segment becomes the basis for the advertising appeal(s) and the copy platform used to communicate with each particular segment. Any differential demographic strength exhibited by a segment further enhances promotional strategy by making it possible to "rifle" an appeal directly at that segment. A bank example is: suppose a segment favors low loan interest and ease of getting loans; if no other segment considers these benefits very important, we can label that market position unique to that segment. We then evaluate patronage habits of that segment, if our bank is perceived as occupying that market position with another bank, or not occupying that segment we can use convenience selective appeals (brand switching) or selective appeals based on adoptive strategy to impress "loan seekers" with our matching our benefits to their benefits sought. The problem of "rifling" this message at them concerns media strategy. Which media (TV, Radio, etc.) and which vehicles, such as TV News shows, TV adventure shows, etc. or magazines, Time, Sports Illustrated, etc., will we use. Based on demographic strengths we can use syndicated media usage data to select our media to match the demographic profile of our "loan seekers." Problems can still occur. If there is demographic overlap, we must amend our appeals to not offend other segments, use secondary media and hope to avoid other segments and still reach our prospects, or just decide which market position is more valuable and choose appeals (copy) and media to maximize our image gains with that segment.

Thus, to adequately describe a market position (segment), we must list its differential benefits sought, demographic strengths, and retail banks favored. Furthermore, we must describe the impressions overall of the banks in the market to know if a firm must change or strengthen its image with a particular segment.

Over two time periods this problem becomes not only measuring these items twice but also tracing segments, individuals, bank images, and patronage habits. Given the number of variables used to describe the market the number of possibilities of outcome over time is astronomical even after the first time period analysis is accomplished. Therefore, the remainder of this section will describe the procedures used to uncover the changes in the market over time.

Uncovering Change or the Lack of it

The first check on the stability of the solution will be simple crosstabulations of the old and new cluster memberships. This will quickly reveal if the individuals in a particular segment form the basis of that same segment in the second time period, given that similar segments in both time periods exist for comparison.

After this anlaysis, presupposing enduring segments, there exists a condition of stability of individual classification or a "cluster switchers" phenomenon. In the case of a "cluster switchers" phenomena, a particular segment in the second time period is made up of individuals from many different segments in the first time period. This would be assumed to mean that the members of a segment in the first period would no longer seek the same benefit(s) in the second time period. The test for this will be several discriminant analyses not only to test the assumption that "cluster switching" results in a change in basic benefits sought by a particular previously homogeneous group, but whether the new classification adequately portrays the new set of benefits sought. Three disciminant analyses will be done. The first will use the old importance vectors as the set of independent variables and the old segment, membership, as the dependent variable. It is expected that the predictive power of this analysis will be high if the cluster analysis in the first time period was a good solution.

The second discriminant analysis will use the new importance vectors as the set of independent variables and the new segment membership as the dependent variable. A priori, the predictive power of this analysis should also be high.

The third analysis will use the old cluster membership scores as the dependent variable and the new importance vectors as the set of independent variables. If there was a "cluster switchers" phenomena, the predictive power of this analysis should be poor as the old classification based on the new benefits sought should not be well classified. However, in the absence of a "cluster switchers" phenomena, namely, if benefits sought remain constant over time at the individual consumer's level, then the predictive power of the analysis should be high.

If the third discriminant analysis reveals good correspondence between both time periods and reaffirms a stability at the individual level first uncovered in the crosstabulation analysis, the market will be judged stable and the analysis ends at that point with the managerial task explained for a stable market.

If, however, the market is unstable, further analysis will be done since a "cluster switchers" phenomena implies that we do not have stable targets for "rifling" our appeals, even though the basic bundles of benefits sought (such as loan seekers) are still ascribed to by similar numbers of consumers. In the case of a stable market, segments or consumer positions in a perceptual mapping approach stay consistant and the entities (banks in this case) of competition move and reposition themselves using stable combinations of appeals and media (rifling tools). In the unstable market, appeals may stay constant but media may have to change based on the demographic makeup of the new consumers in each segment. This demands a crosstabulation of new segment membership with demographic and SES variables to reveal differential advantage in media usage.

Summary

This chapter has described the data base to be used and reviewed previous methodological approaches to benefit segmentation analysis. Problems lacking empirical evaluations in the use of data inputs and algorithm choice were revealed and empirical analysis to solve the methodological questions was evolved and proposed. The stability of the solution resulting after the analysis in a single time period was questioned and comparison with an identical analysis to be done on a later measurement of the same gorup of consumer was proposed. Possible general managerial strategy was outlined as a motivation for questioning market stability. Chapter IV will be the analysis of the first two research questions and the analysis of the 1972 wave of data. Chapter V extends the analysis to the second time period and evaluates the stability of the market.

CHAPTER IV

RESULTS OF BENEFIT SEGMENTATION ANALYSIS

In this chapter, the first two research questions which were first proposed in Chapter I will be answered and the bank market which was described in Chapter III will be analyzed using the first time period data. Initially, the factor analysis of the importance vector will be described to show the perceived underlying dimensions of bank attributes, and then the factor scores, along with the three other data types (described in Chapter III), will be evaluated for consistency in the clustering solution. Next, the solutions of the three different clustering methods (described in Chapter III) will be compared as to consistency, discriminability of real and random data, solution of clustering level, and managerial usefulness. The solution deemed best according to the above criteria will be chosen, and the market structure and segmentation strategy will be described.

The Factor Analysis of the Bank Attributes

A factor analysis was performed on the bank attributes using the seventeen importance variables described in Chapter III. The results were rather clear cut and consistent in both split halves of the data. This was evidenced by the fact that the same number of factors were extracted, based on eigenvalues greater than one, and the same variables loaded heavily on the same factors in both split halves. Given these indications of consistency, a run was performed on the overall sample and, as expected, the result was extremely similar to each split half result. The overall (combined over both halves) factor analysis is shown in Table 1. The four factors were named "convenience and value," "loans," "facilities," and "size and advertising" as these names gave an indication of the apparent underlying dimensions represented by the factors.

Next, factor scores were computed for each individual and these were one of the inputs submitted to the Howard-Harris clustering algorithm.

Comparison data inputs. As mentioned in Chapter III, four data input types were available for each individual. These were raw data, data standardized by row, standardized by column, and factor scores. These were compared as to consistency of solution using a chi square measure on comparability of group size over split halves and a comparison of Pearson r's between average scores from similar groups between each split half. The results are shown for solutions averaged over grouping levels of two through ten groups in Table 2. As can be seen, raw data and factor scores yield similar levels of consistency on both measures. Also, both methods of data input are better in the sense of having the lowest chi square values, and the highest r's.

Given the empirical evidence, standardization by row and column will be rejected as inputs. The remaining choice is between raw data and factor scores. Factor scores will be chosen as the input for several reasons. First, on the original criterion of consistency factor scores were almost identically consistent as raw data over split halves. Second, it is intuitively more sound to use a data set without redundancies in measured attributes as input to cluster analysis. Finally, the use of factor scores to group individuals allows the use of tests of significance between groups using the original raw data. As Morrison (1967) points out, an assumption required for testing the significance of differences between groups is that the data used in the test was not the data used to group the individual entities in the first place.

Comparison of the Three Cluster Methods

Consistency. Using factor scores as input data, the three clustering algorithms were compared on consistency of solution. As explained in the previous chapter, x^2's and r's were computed over split halves and compared for the three algorithms. The results appear in Table 3. It is fairly evident that, on the criterion of reproducible group size over split halves, Howard-Harris was superior and Johnson was inferior. TAXMAP gives a seemingly intermediate result; this can be explained by the monothetic property of the algorithm resulting in many very small groups in the final solution.

In comparing the r's, Howard-Harris again is best but TAXMAP has the lowest correlation between split halves using group means of the original seventeen variables. Johnson's result of .66 was not much better than that of TAXMAP. With TAXMAP, its monothetic properties were once again the source of the poor result. No algorithms will be dropped from the analysis at this point, but will be tested as to ability to distinguish solutions from real and random data.

Discriminability of the three algorithms using real and random data input. As discussed in Chapter III, F-ratios will be calculated for each variable to check the difference between groups on each level of grouping for each split-half. TAXMAP has only one level of grouping, hence, the F-ratios will only be computed for that level. As previously discussed, following a suggestion of R.M. Johnson (1972), algorithms which discriminate well between real and random data show this sharply in the F-ratios computed on the cluster solutions. Table 4 presents the results of this analysis.

The first row indicates the average F-ratio for the 17 importance ratings. Since the data was analyzed on a split half basis, this average represents 34 ratios in the case of TAXMAP and 306 ratios for Johnson and Howard-Harris. Both Johnson and Howard-Harris presented uniformly decreasing average F-ratios at each of nine cluster levels and since the average percent difference between methods was almost uniform ($\pm 2\%$), the average comparison was used.

In comparing the three algorithms, Johnson was clearly the poorest. For the Johnson algorithm, the ratios for the random data were 71 percent as high as for the real data. Whereas, for Howard-Harris, they were only 26 percent as high and for TAXMAP were only 18 percent as high. Thus, on the ability to give as solution which can be discriminated from a random solution, Johnson cluster seems poorly suited to this data set. Thus, it will be excluded from further analysis.

Solution of cluster level for Howard-Harris. As proposed in Chapter III, F-ratios were examined to see if a solution can be found as to which member of groups is a "final" solution to Howard-Harris clustering algorithm. This is illustrated in Table 5. Average scores are reported for both split halves and all 17 variables at each level. It is interesting to note that all variables are significant at all levels for each split half ($p \leq .001$). Thus, the idea of using the number of significant F-ratios at each level is useless for this data. Also, the rate of decline in F-ratio as the number of groups rises seems to be rather uniform, hence a sudden decrease in explanatory power does not occur as the number of groups increases. Therefore, an examination of F-ratios alone does not yield a solution of what level to cluster at.

Rand (1971) suggests that a good cluster solution might be one where two different algorithms give similar answers. TAXMAP produced an output consisting of five large clusters and many smaller clusters containing very few consumers. The profiles of the large clusters corresponded well with the profiles of the clusters in the five group Howard-Harris solution. As will be shown the five group Howard-Harris solution also seemed managerially interpretable and each cluster seemed to favor a particular retail outlet. Thus, the five group solution was selected and will be explained in the next section.

The Howard-Harris solution was selected over the TAXMAP solution since it was polythetic and thus yielded several large groups as contrasted with the monothetic TAXMAP solution which yielded five large groups in each split half solution but also yielded many small groups of two, three, or four consumers who had unique sets of responses to the importance measures. The TAXMAP solution was very difficult to use managerially and due to the small number of consumers in each group, any conclusions based on the small groups was suspect. Lessig and Tollefson (1971) found similar solutions with monothetic methods on coffee consumption panel data (eight main clusters and 52 additional groups) and Peterson (1974) states that when similar results on the main clusters occur, a polythetic solution is more desirable and superior to a monothetic one for managerial purposes.

Description of market segments found. An overall chart of differences between benefit segments is shown in Table 6. The five benefit segments were labeled front runners, loan seekers, representative subgroup, value seekers, and one stop bankers based on the combination of benefits sought by the group. Each segment will be described with possible copy and media strategies for each will be presented.

Front runners. This segment sought (large) size of bank, bank for all, a bank that did a lot of advertising, and a modern bank. This was the smallest benefit segment but remained distinct at even a cluster level of three groups despite a very small size (n=11). This group favored the largest, most modern, and most heavily advertised commercial bank as evidenced by the fact that all eleven people in the group had at least one account there and nine had more than one account there. Demographically, they were younger than average, rented their living quarters, and were in the area a short time as shown by crosstabulation analysis.

Strategically, this group is very small, only comprising three percent of the market and favors the largest commercial bank. Demographically, they are young people, new to the area, and would seem to be good prospects for any bank. However, they do not have above average education nor occupations which make them a highly desirable customer at this point in time.

Loan seekers. Loan seekers were consumers who valued good reputation, encourages financial responsibility, easy availability of loans, low loan interest, and friendliness as important benk benefits. This group was concerned with the availability and cost of credit. They had higher than average incomes and smaller than average household size. They tended to move more often than average; however, they remained within the general area. This group tended to favor commercial bank two which was of considerable size and savings bank one which was very small, but which heavily advertised lending services.

This group did not display any unusual demographic strengths which would allow them to be targeted by specific media which is always a problem with local media. However, the benefits they sought, especially on the loans dimension, clearly set the basis for advertising copy directed at this group, which comprises 17 percent of the market.

Representative subgroup. This was the largest of the benefit segments, comprising 38.7 percent of the market. This group was interesting in that the responses to the benefits sought questions were all about average. On no scale did this group tend toward the extremes from the population average. This group remained mostly intact at clustering levels of three through eight groups (only 5% differential loss). They favored the largest commercial banks, especially for checking and credit card services. Otherwise, nothing distinguished them on the average from the population as a whole. In the benefit segmentation context, there are no managerial conclusions to be drawn for the largest segment. This seemed peculiar so all previous clustering solutions using this data bank were examined and it was found that a similar group existed in all solutions of six groups or less (consistent over split halves) and most solutions of eight groups or less. Furthermore, varying the type of input data (for example, standardization by row or column) did not substantially affect this phenomena.

Furthermore, informal discussions with several private consultants, who wish to remain anonymous, have revealed a similar phenomena with bank customers in their studies.

Value seekers. Value seekers comprise 17 percent of the market. They consider high savings interest, quick service, and low loan interest to be of principal benefit to them. They tend to patronize the two largest savings banks more than other banks, perhaps due to a higher savings interest differential which existed and was loudly proclaimed in advertising at that time.

They were conservative in their outlook on life in general and also in their view as to how easily credit should be given and the use of credit cards. They tended to own their own home, were slightly older than the average, lived in the area longer than average, and the husband's occupation tended to be blue collar.

This group offers opportunity to the commercial banks as they can be targeted well on their home ownership, time in area, occupation, and age. The copy appeals should naturally emphasize value.

One stop bankers. One stop bankers were the second largest segment, comprising almost 28 percent of the market. They sought wide variety of services, high savings interest, convenient hours, parking, quick service, and availability of loans. They favored commercial bank one in practice but also made good use of commercial bank two.

Demographically, there were very few distinguishing characteristics except for an absence of minority ethnic people. On banking AIO's, they were lower than average on the money management, loans, and credit dimensions.

This segment has strong basis for advertising appeal since the group seeks convenience and value but apparently is ill at ease in making banking decisions or is too busy to devote much time to them. However, targeting becomes a problem since only one very weak indicator separates them from the population at large and that is an underpresentation of minority persons.

Summary

This chapter presented the results of the benefit segmentation analysis proposed in Chapter III and answered the first two of the three major research questions regarding benefit segmentation methodology.

A factor analysis uncovered four principal underlying dimensions in the seventeen importance scales used to measure benefits sought in the market. Factor scores, raw data, data standardized by row, and data standardized by column were compared as to consistency of cluster solution produced by the Howard-Harris clustering algorithm. Factor scores were chosen due to higher consistency and the possibility of still using the raw data for F-tests without violating statistical assumptions which preclude using the data used to form the groups from being used to test the group differences. Thus, the first research question: "Which data procedure is most consistent over split halves of data and gives the most clearcut solution in benefit segmentation," has yielded an answer of factor scores.

The next step was algorithm choice from Johnson cluster, Howard-Harris cluster, and TAXMAP. On consistency, measured by chi-square and Pearson product moment r's, correlations (r's) Howard-Harris was a superior solution. In terms of the F-ratios uwed to discriminate between real and random data, Howard-Harris and TAXMAP were clearly superior. On ability to come to a final solution, TAXMAP had a built in procedure which worked, while the proposed solution of using F-ratios to detect a final solution for Howard-Harris failed to work. A comparison of solutions between TAXMAP and Howard-Harris at this point for managerial usefulness led to a choice for Howard-Harris due to the inability to use the monothetic TAXMAP solution managerially. Finally, a basic solution to five groups was chosen from the Howard-Harris solutions solving the second research question concerning choice of algorithm.

The benefit segments were described and the implications for copy were presented. Grand strategy including media targeting was frustrated due to poor demographic differences between segments. Currently, demogrpahics are the best way of targeting media. No significant lifestyle pattern appeared which could be used for media targeting and this, coupled with the lack of collected media data on the first wave, prevented a computation of relative cost of penetration for each segment.

The next chapter will evaluate any changes in the segments over time and possible managerial considerations.

Table 4.1

Overall Factor Analysis 1972 Data

(Factor Loadings after Varimax Rotation and Kaiser Normalization)

	Factor 1	Factor 2	Factor 3	Factor 4
Large	-.004	-.069	.215	.541
Wide Variety Sucs	.330	.318	-.046	.371
Does Lot of Advertising	.041	.219	.161	.641
Convenient Branches	.692	.140	.005	.149
Good Reputation	.552	.252	.129	.261
High Savings Interest	.685	.187	.103	-.044
Modern	.011	.002	.548	.353
Pleasant Offices	.199	.156	.661	.149
Encourages Financial Responsibility	.305	.399	.432	.165
Convenient Hours	.813	.166	.085	.043
Community Concern	.406	.324	.396	.070
Parking	.493	.030	.280	.084
Friendly	.545	.379	.295	-.014
Loans Available	.126	.790	.119	.083
Quick Service	.694	.320	.181	-.106
Low Loan Interest	.395	.685	.018	.010
Bank for All	.229	.414	.241	.170
Eigen Values	5.508	1.374	.843	.573
% of Variance	66.4	16.6	10.2	6.8
Apparent Underlying Dimension	Convenience and Value	Loans	Facilities	Size and Advertising

Note: All figures rounded to 3 decimal places.

Table 4.2

Comparison of Data Inputs to Howard-Harris

(Averaged Over Grouping at Levels Two Through Ten)

	Average X^2	Average r's
Raw Data	19.68	.94
Standardized by Row	32.18	.78
Standardized by Column	21.09	.81
Factor Scores	18.44	.93

Table 4.3

Comparison of the Three Clustering

Algorithms for Consistency

(Johnson and Howard-Harris Averaged over Grouping at Levels Two through Ten)

	Johnson	Howard-Harris	TAXMAP
Average x^2	55.06	18.44	32.01
Average r's	.66	.93	.56

Table 4.4

Comparison of the Three Clustering Algorithms

For Real and Random Data Discriminability

(Johnson and Howard-Harris Averaged over Grouping at Levels Two through Ten)

		Johnson	Howard-Harris	TAXMAP
Average F-Ratio	Real Data	9.23	27.66	38.06
	Random Data	6.54	7.14	6.88

Table 4.5

Average F-Ratios at Each Level of Grouping for Howard-Harris

Number of Groups	Average F-Ratio
2	42.90
3	37.42
4	32.18
5	27.88
6	25.30
7	22.70
8	21.35
9	20.30
10	18.97

Table 4.6

Bank Market Description*

Segment	1	2	3	4	5
Name:	Front Runners	Loan Seekers	Representative Subgroup	Value Seekers	One Stop Bankers
Principal Benefits Sought	-Large -Bank for all -Does a lot of advertising -Modern	-Good reputation -Encourages financial responsibility -Loans easily available -Low loan interest -Friendly	-About average on all benefits sought	-High savings interest -Quick service -Low loan interest	-Wide variety of services -High Savings interest -Convenient hours -Parking -Quick service -Loans available
Banks Favored	Commercial Bank #1	Commercial #2 Savings #1	Commercial #1 Commercial #2	Savings #2 Savings #3	Commercial #1
Demographic and SES Characteristics	-Younger -Rent home -Less time in area	-Higher than average income -Smaller household -More transient	-None	-Tend to save more -More time in area -Blue collar	-Less minority
Lifestyle (AIO)(dimensions showing general strength		Credit (H) Loans (H)		Conservative (H) Credit (L)	Money Management (L) Credit (L) Loans (L)
Size* (n)	11	59	119	58	96

*Since consistency was high between both split halves, the analysis shown here represents the overall sample.

CHAPTER V

STABILITY OF BENEFIT SEGMENTATION SOLUTION OVER TIME

This chapter extends the analysis of the banking market into a second time period. Three discriminant analyses will be done to ascertain whether any change has occurred in the market segmentation structure, and to isolate the causes of the apparent change. If no change occurs in the combination of benefits sought by the customers analyzed, the classification of customers into groups should be as good using the measurements obtained in the second time period as is obtained using the measurements of the first time period. If not, further analysis will be done on the second period data. First, the data will be analyzed to see if the same type of segments exist, whether there is a "cluster switchers" phenomena, and whether classification rules can be devised that work in the second time period. Also, an examination of demographics in the second time period will reveal any possible improvement in the use of such variables for media selection.

Classification Analysis of the First Time Period

A set of classification rules were derived by means of a multiple discriminant analysis. The discriminant analysis was set up with cluster membership as the dependent variable and the seventeen sought benefits as independent variables.

The first analysis was done using the two split halves of the 1972 data. Each split half was used to derive a set of discriminant functions and the other split half was used to check the correctness of the classification procedure. As shown in Table 1, 84.5 percent of the cases overall were correctly classified.

Thus, one may derive a set of equations which will correctly classify the 1972 respondents into the benefit segments to which they belong.

Analysis of the 1974 Data

The main question to be answered is: "Is the solution stable over time?" There are several ways this can be approached. First, a benefit segmentation analysis was done which was identical in design to the analysis done on the 1972 data. The results of the cluster analysis once again indicated a five group solution. As shown in Table 2, the results are very similar to the results from the 1972 wave of data. The types of segments based on benefits sought are virtually identical to those in the first wave and are of relatively the same size as in the first wave. Thus, for the purposes of advertising copy, marketing strategy will be the same. Furthermore, classification of individuals into groups using the benefits sought in 1974 permits a classification accuracy of 88.7 percent as shown in Table 3.

The second part of the marketing strategy is media selection. The 1974 wave had measures of media habits and for most segments, some differential habits were found which would facilitate media selection.

Demographics showed a small change between waves. This result implies there was some "cluster switching." The appearance of this phenomena might show a need to change media policy from the previous period.

The next section will investigate the changes at the individual level which are not apparent at the segment level.

The Cluster Switchers Phenomena

A "cluster switchers" phenomena is a condition where, over time, an individual will change the importance of the various attributes or benefits sought so as to move to another market segment. One good test for this is to attempt to classify individuals into their original segments using their new set of benefits sought. Table 4 shows the overall results of such an analysis on the two split halves of data. Using the 1974 sets of benefits sought only 44.8 percent of the consumers were correctly classified into their 1972 market segments.

Table 5 reveals the true extent of the "cluster switching" phenomena, only 28.8 percent of the consumers remained in the same segment they were in during the first wave of analysis. Even if the process were completely random, 20% would be expected to remain. This shows that, although the relative desirability of various benefit bundles remained stable over time, the individuals seeking those sets of benefits changed. Due to the unavailability of media habit data for the first time period analysis, an assessment of the need to change media strategy must be based on observed demographic changes. The use of demographics for the targeting of media becomes almost impossible to do scientifically when the demographic profiles over time change. The added problem is the inability to decide <u>when</u> to change strategies.

This result raises many questions concerning when these shifts occurred and leaves one with the feeling of analyzing snapshots of a moving phenomena. A conservative judgment would be that, although the set of copy appeals used to reach each segment should remain constant, the media strategy should be carefully monitored to keep up with what appears to be a moving target at the individual level.

Summary

Classification accuracy for each of the benefit segmentation solutions was examined and found to be high. However, the classification rules were not stable over time at the individual consumer level, despite considerable support at the aggregate segment level in reference to sets of benefits sought.

A "cluster switchers" phenomena was revealed which had serious implications for media strategy.

Chapter VI will summarize the whole study and present directions for improving future studies of this type.

TABLE 5.1

Prediction Results of Discriminant Analysis Using 1972 Data

Actual Group	Number of Cases*	Predicted Group Membership 1	2	3	4	5
1	10	10	0	0	0	0
2	56	0	45	2	0	9
3	118	0	5	110	1	2
4	52	0	1	0	44	7
5	93	0	14	4	6	69

84.5% of cases correctly classified

Chi-square = 855.411   Significance ($p < .001$)

*Does not add exactly due to partial missing data.

TABLE 5.2

1974 Bank Market Description*

Segment	1	2	3	4	5
NAME:	Front Runners	Representative Subgroup	Loan Seekers	Value Seekers	One Stop Bankers
Principal Benefits Sought	-Large -Bank for -Does a lot of advertising	-About average on all benefits sought	-Good reputation -Loans easily available -Low loan interest	-High savings interest -Quick service -Low Loan interest -Plenty of parking	-Wide variety of services -Encourage financial responsibility -Convenient hours -Quick service -Convenient branches
Banks Favored	Commercial Bank #1	Commercial #1 Commercial #2	Commercial #2 Save #1	Save #2 Commercial #2 Save #3	Commercial #1 Commercial #2
Demographics & SES	-Young -Rent home	-None	-More transient -More blue collar	-Tend to save more	-Older
Lifestyle(AIO) (dimensions where general strength was shown)	Money Management		Loans (H) Credit (H)	Conservative (H) Credit (L) Risk Taking(L)	Checking Account Usage (H) Credit (L)
Differential Media Strengths	TV Sports	About Average	Adventures (TV) Newspapers Sports	Midday Radio	Television Serials Evening FM Radio
Size*(n)	8	118	51	89	78

*Since consistency was high between both split halves, the results shown here represent the overall sample.

TABLE 5.3

Prediction Results of Discriminant Analysis Using 1974 Data

Actual Group	Number of Cases*	Predicted Group Membership 1	2	3	4	5
1	8	8	0	0	0	0
2	118	0	103	3	6	6
3	44	0	2	37	5	0
4	89	0	5	7	77	0
5	77	0	4	0	0	73

88.7% of cases correctly classified

Chi-square = 990.860 Significance ($p < .001$)

*Does not add exactly due to partial missing data.

TABLE 5.4

Prediction Results of Discriminant Analysis

Using 1974 Data and 1972 Membership

Actual Group	Number of Cases*	Predicted Group Membership 1	2	3	4	5
1	11	5	1	3	1	1
2	57	8	29	6	5	9
3	117	16	12	61	14	14
4	56	11	8	11	20	6
5	95	19	20	18	6	32

43.8% of cases correctly classified

Chi-square = 118.453 Significance ($p < .001$)

*Does not add exactly due to partial missing data.

TABLE 5.5

Switching Matrix to Reveal Cluster Switchers

1974 Groups

		1	2	3	4	5
1972 Groups	1	1	3	1	4	2
	2	2	21	18	14	5
	3	3	47	9	10	50
	4	0	11	13	23	11
	5	2	36	10	38	10

28.8% remained in their respective segments over the two waves of measurement.

CHAPTER VI

SUMMARY, CONCLUSIONS, AND POSSIBLE DIRECTIONS FOR FUTURE RESEARCH

Summary

This study was undertaken to examine the methodological considerations relevant to benefit segmentation. The basic orientation as set forth in Chapter I was managerial contribution rather than as an addition to consumer behavior theory. A review of the literature revealed that the vast majority of the segmentation literature has been devoted to the academic or "consumer theory building" types of studies, while very few empirical managerially oriented studies have appeared.

With several past benefit segmentation studies as a guide, a flow chart was evolved detailing the steps of a typical benefit segmentation study. After a detailed examination of this set of procedures, several research questions were proposed concerning data input type to a clustering algorithm, type of clustering algorithm to be employed, and stability of the solution over time. It was proposed that empirical validation of the research procedures would strengthen the execution of the benefit segmentation concept.

Many studies which used econometric methodology were examined and very little evidence supported their continued use. Several other studies were uncovered such as Monroe and Guiltinan's (1975) study which used crosslagged correlations to describe consumer paths as a method of typifying buyers. This latter article as well as a few others showed the importance of time as a criteria in market segmentation studies.

Therefore, stability over time was added as a criterion for market segmentation to other criteria proposed by Wilkie (1971) which specified "homogeneity within and heterogeneity between groups, usefulness as a correlate of behavior, and efficiency as a target for marketing tools."

Thus, taking benefit segmentation as a starting point and borrowing insights, such as longitudinal evaluation, from other studies, a more exhaustive benefit segmentation methodology was subject to empirical evaluation. The improved approach was centered around three major research questions:

1. Which input data procedure is most consistent and gives the clearest solution in benefit segmentation analysis?
2. In the benefit segmentation context, what rules should govern the choice of clustering algorithm, and how sensitive is the solution to algorithm choice?
3. Is the benefit segmentation solution stable over time?

All three research questions covered substantial holes in the literature regarding benefit segmentation methodology.

The data used was collected from a consumer panel in a large midwestern city focusing on the retail banking market. Six major banks accounted for virtually all retail banking within the city, thus eliminating outside competition as a source of error. During two time periods households were measured on attitudes towards each bank, benefits sought, general and banking lifestyles, demographics, and patronage of various banking services. The two waves were collected in 1972 and 1974, and a split half design was used throughout to provide a consistency validation.

Four data types were analyzed as inputs to cluster analysis. Raw data, data standardized by row, data standardized by column, and factor scores of each consumer's benefits sought vector were evaluated. Raw data and factor scores yielded more consistent solutions to the cluster analysis as evidenced by higher reproducibility over split halves of data. Factor scores were finally chosen since they are orthogonal, non redundant, and allow tests of significance on final cluster solutions without violating statistical assumptions which require that the data used to test group differences were not used to group the individuals.

Three cluster methods were used to group individuals into segments based on benefits sought. The Howard-Harris routine was most consistent over split halves with TAXMAP and Johnson cluster giving less consistent results. When tested on ability to discriminate real and random data using F-ratios, Johnson cluster was quite poor and dropped from further analysis since random data F-ratios were 71 percent as high as for the real data. F-ratios were examined as a possible solution as to final clustering level for the Howard-Harris algorithm. This approach failed to lend any insight into the solution level problem,and a good solution was judged to be the one which was common to both algorithms, even through they utilized different approaches. A five group solution was chosen since the underlying benefits sought by the large clusters over split halves and algorithms. The Howard-Harris solution was chosen over the TAXMAP solution because the polythetic Howard-Harris routine yielded five large clusters which were managerially interpretable,and each cluster favored a distinctive set of retail outlets fulfilling several of the previously mentioned criteria. The TAXMAP monothetic solution yielded similar large groups but additionally resulted in many small groups of two, three or four consumers who sought a unique set of benefits and were too small and diverse to profitably influence managerial strategy.

The market structure was consistent over split halves,and the combined results were presented. The five groups were labeled "front runners, loan seekers, representative sub-groups, value seekers, and one stop bankers." The differential benefits sought, banks favored by patronage, lifestyles, and demographics of each segment was presented and advertising appeals (copy platforms) based on differential benefits sought were proposed. Targeting of each segment by mass media was attempted using demographics but proved very difficult and suspect since demographic differences were not pronounced and differential media use data based on demographics in local areas is not always available and/or accurate.

Thus, the static analysis resulted in a use of factor scores as input and the use of the Howard-Harris algorithm based mainly on the criteria of split-half reproducibility, managerial interpretability, and usefulness of segments as market targets.

The third major research question concerned the stability of the solution over time. Classification rules were derived using discriminant analysis on the first time period and a very successful result was achieved. The same result occured when a duplicate type benefit segmentation analysis was performed on the 1974 data. The only change observed was a slight change in the demographic profiles of the segments in the second time period.

Further investigation uncovered a "cluster switchers" phenomena where, over time, individuals changed the importance of the various attributes or benefits sought so as to change groups. Thus, despite the appearance of almost identical segments in both time periods there were a substantial number (71.2 percent) of individuals who changed groups over time. Thus although the relative desirability of various benefit bundles remained constant, the individuals seeking those sets of benefits changed.

Conclusions

The three major research questions were successfully operationalized and methdological rigor was applied and empirical justification was attempted. Methodologically the major improvements were the use of the split half design improving the consistency validity of the benefit segmentation procedure, the evaluation of alternative data inputs bringing advancements noted in academic type studies such as Meyers and Nicosia (1968) and Green and Rao (1969) to an ostensibly managerially oriented procedure, and the application of various rules of thumb to the choice of a clustering algorithm in a managerial context. Thus, many "seat of the pants" managerial procedures can be evaluated empirically and methdologically justified.

The third and last research question was operationalized, and the answer uncovered a situation which leads us back to consumer theory questions, such as dynamic typologies, last evaluated as a point of departure in Chapter II. It was found that two static benefit segmentation analyses of a retail bank market in a closed economic environment were virtually identical, despite the fact that measurements were taken two years apart. Obviously, many stimuli were exerted on the individuals in that market. These stimuli eminate from the banks, in the form of marketing mix efforts, and from the environment, in the form of economic conditions, income changes, and other market changes. These considerations were not fanciful as evidenced by the fact that only 28.8 percent of the individuals remained in their corresponding first period segment in the second time period. Furthermore, one never knows if these people moved every day, week, month, or year in their bundles of benefits sought from banks. A fairly strong case can be made that benefit bundles are stable at the segment level and therefore basic copy platforms should remain constant. However, media policy is virtually impossible from this type of result. Not only does everyone change, but we are left with the hopeless feeling that perhaps the entire analysis is suspect, aside from copy policy, since dynamism is such an apparently crucial part of the market at the individual consumer level.

Directions For Future Research

These previous conclusions lead to an approach which would incorporate the apparent dynamics of the market into the analysis. To prevent absolute chaos, we will assume that, like traditional static benefit segmentation analysis, we will proceed as usual to identify segments based on benefits sought supported by differential patronage of those institutions or brands which best match up with the set of benefits sought. This is less of a problem if self selection is used to target appeals. There may be improved ways of measuring the benefits sought as mentioned in Chapter I (R.M. Johnson, 1972; Green & Carmone, 1970; Green & Rao, 1972) and are determined in actual application by constraints of cost, respondent fatigue, instrument accuracy, investigator competence and breadth of experience with scaling methodology and/or clinical psychology methods, and degree of competition on service/product differentiation refiled to each segment. Therefore, the primary aim is to implicate advertising copy directly by a successful segmentation of the market. To continue the basic approach then calls for continuous campaign monitoring for endogenous changes brought about by advertising efforts and exogenous or "environmental" effects. Also one may move to derived measures rather than direct measures (R.M. Johnson, 1972; Green & Carmone, 1970).

If one utilizes Stefflre's framework (as outlined in Chapter I), and built up a model to measure the links between market communications and individuals' ideal points in a joint product/benefit/person space, one would _expect_ individuals to show change. Since the product and person positions are both affected by communications based on the benefits which are the inputs _and_ outputs of the anlaysis. Thus the phenomena of change, which is a relative nuisance in a managerial sense, can be the basis of a fruitful insight into consumer behavior. Examples are Blattberg and Sen's (1974) article and Monroe and Guiltinan's (1975) study both using dynamic situations to describe market behavior.

One possible starting hypothesis is the need for variety first mentioned by Reynolds (1965). Reynolds expressed the view that over time people might change merely to widen their range of brand and product experiences. He felt that consumers would increase their satisfaction due to a wider knowledge of market alternatives. By using this as a starting point one might discover switching as a natural market phenomena in certain product classes.

A series of experiments could reveal whether there are changes in benefits sought in a market due to exogenous factors alone, which never can really be controlled anyway, i.e. a "non-experiment," to identify one possible source of variation. If there isn't any change due to exogenous factors alone, one could proceed to an experimental condition of communication by one brand/firm and observe the changes and then at least have a theoretical perspective to begin hypothesizing about the "cluster switchers" phenomena.

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