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TARGETING THE SWITCHABLE INDUSTRIAL CUSTOMER

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This article presents a new approach to target marketing. An industrial market for electrical equipment is segmented on the basis of the *strength* of current preferences as defined by the probabilities of selecting the various suppliers. A modification of a disaggregate attribute choice model (logit) is used to identify the firm's "switchable" customers. The "switchable" customers are then targeted by direct personalized mail and visits by a "missionary" sales force. A major supplier of large-scale electrical equipment utilized this methodology with impressive sales results.
(Industrial Marketing; Choice Models; Brand Switching; Supplier Loyalty)

1. Introduction

Brand loyalty, implying the strength of preference for a particular product or product line, is a well-known and heavily researched topic in the field of consumer marketing. An analogous concept to brand loyalty in the field of industrial marketing is "supplier loyalty" implying the strength of preference for a particular supplier. The purpose of this article is to suggest a practical managerial strategy which uses the concept of supplier loyalty as the critical dimension in allocating the marketing effort of the firm. A basic marketing decision which all firms must answer implicitly or explicitly is how much of the marketing effort should be directed at customers already favoring the firm and thus likely to buy from it versus the proportion of marketing effort used to attract new customers. Depending on the firm's goals, competitive environment, and perceptions of current and future market segments various strategies are implemented. A practical requirement for developing a marketing strategy that considers supplier loyalty is the ability to *measure* the strength of supplier loyalty of each customer and/or to segment the total market into various segments of supplier loyalty.

For frequently purchased goods such as paper towels, coffee, and soap brand loyalty has been measured in terms of past purchasing patterns (Kuehn 1962; Frank 1967; Blattberg and Sen 1976). However, the use of past purchasing records is not intuitively appealing for durable goods and many large ticket industrial products. The longer buying cycles, often more than a year in length, allow for time in which criteria, perceptions, experience, and often the set of actual decision makers at the customer's firm may change and thus destroy the stationarity assumption underlying the use of past purchase patterns.

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This article suggests a method of obtaining a reasonable measure of supplier loyalty for industrial products and durable goods. The method proposed is to look at the significance of the differences in the choice probabilities generated by the multinomial logit choice model. The computer programming required to add this extension to existing logit algorithms is simple and straightforward. A major industrial firm utilized the proposed methodology to develop a marketing strategy which resulted in some rather impressive sales results. The following sections will review literature on supplier loyalty, describe the industrial case situation, the methodology, the data analysis, results, and general conclusions.

2. Literature Review

Wind (1970) was the first to examine supplier loyalty for industrial products. He investigated the purchase of inexpensive components (7¢ to $117) for an electronics firm. Perhaps because components tend to be standardized there was little investigation of product features. Wind found empirical evidence that supplier loyalty exists using primarily organizational variables, attitudes, price, and work simplification variables. Much of the subsequent work in analyzing industrial purchasing has focused primarily on the organizational relationships within the buyer's organization (i.e. positions and experience of individuals in the buying firm involved in the purchase decision), Hayward (1972), Czepiel (1974), Choffray and Lilien (1978), Spekman and Stern (1979), and Robertson and Wind (1980). A good review of these articles is provided by Thomas and Wind (1981).

Wind (1978) in reviewing the literature on organizational buying behavior states "Surprisingly, despite the numerous academic and commercial organizational buying behavior studies, one can draw very few substantive generalizations as to which variables would have what effect under what conditions." Given the complexity of obtaining and aggregating meaningful measurements of each buyer organization's structure and interactions, considerably more research must be done before practical applications predicting relative strength of preference or market shares for a set of suppliers as a function of organizational variables can be expected.

This study will diverge from the established approach of analyzing supplier preference as a function of organizational variables. Instead, relative supplier preference will be predicted as a function of product attributes and supplier services. The electrical equipment industry, described in the next section, is one in which there is extensive product differentiation. Suppliers usually customize their product to best meet the buyer's specifications. The set of support services offered by the various suppliers varies in both content and quality. Thus our behavioral assumption is that buyer's preference for various suppliers is in this case strongly influenced by the product attributes and relative services offered by the supplier.

3. Industrial Case Situation

The consumption of electricity in the United States has an annual growth rate of less than 3% for the last decade. The electrical equipment industry is a mature industry in which total annual sales follow a cyclical pattern, but have a linear trend value that equals the annual growth rate in the consumption of electricity. The industry is currently highly overcapacitated, due in large part to the lack of new housing construction, with total industry sales declining the last three years. Thus any major supplier who attempts to maintain or increase current sales or in the long run to increase sales beyond the 3% level must take these sales from competitors. Any substantial, visible increase in marketing expenditure is observed by competitors and generally triggers a vigorous response, often in the form of a disastrous price war.

The customers consist of investor-owned electrical utilities, rural electrification cooperatives (REC's), municipalities, and industrial firms who purchase transformers, switchgear, and other electrical components for the purposes of generating or distributing electrical power. The electrical customers have, through personal interactions and past experiences, developed varying degrees of loyalty to various suppliers. Conceptually, our supplier firm would like to identify the switchable and competitive segments of current customers. A "switchable" customer is defined as one who currently perceives the firm to be very close to its first choice supplier; a "competitive" customer is defined as one who, while he currently perceives our firm as his first choice, perceives other suppliers as being very close to our firm. These two segments of customers are believed to be the most responsive to the relative marketing efforts of the suppliers.

Ideally, the firm would like a current reading on customers' perceptions of the various suppliers. In addition, the firm would like to know which are the important dimensions influencing perception and how the firm is perceived relative to other firms on these important dimensions. The following sections describe how a firm attempted to gain these insights by analyzing survey data with a modified version of an attribute choice model.

4. Estimating Individual Probabilities of Choice

Marketing is a field which has made extensive use of disaggregate attribute choice modeling in attempting to understand *which* alternative and *why* the chosen alternative is selected from a given set. The current "state of the art" for simultaneous compensatory attribute choice models in marketing includes the sinusoidal functions such as logit and probit (Doyle 1977; Green 1978; Punj and Staelin 1978; Rao and Winter 1978; Gensch and Recker 1979; Flath and Leonard 1979; and Currim 1981) incorporating the concepts of thesholds, diminishing returns to scale, and saturation levels within the choice structure.

The customer's degree of supplier loyalty is defined in terms of his probability of selecting each of the alternative electrical equipment suppliers. These individual probabilities can be generated by choice algorithms operating at either the individual or disaggregate level. Individual level models, in which each individual is fit with a distinct model, range from protocol derived models to statistically fitting a model using n repetitions of the choice by the individual. Given the problems of getting industrial customers to agree to generate protocol data, as well as the time and cost involved in developing between two and three thousand individual models, the protocol approach to individual models is deemed impractical for this project. The individual level model which uses survey or panel data to statistically estimate a separate function for each individual in the sample generally requires n repetitions of the choice process. If the researcher wishes to have a large sample ($n > 30$), the requirement of independent repeat measurements by an individual is an infeasible task for products of interest with long purchase cycles. Batsell and Lodish (1981) suggest parameterizing the choice model on various subsets of the available alternatives as a method of increasing the data usage, but even with the use of subsets Batsell and Lodish indicate that the data requirement is a major weakness of the individual level approach.

Considering the data requirements, it is not surprising to observe that in practical applications choice models almost always estimate parameters, statistically test the parameters, and validate the predictive model at the disaggregate level. A *disaggregate* choice model, as defined by McFadden (1976), is a model which uses individual level data to estimate *one* set of parameters for the population (i.e., logit coefficients). Individual level predictions are made using the one estimated set of parameters in conjunction with value ratings on the predictive variables supplied by the individual.

At the population level it is assumed that the individuals in the calibrating sample are relatively homogeneous with respect to the estimated set of parameters. This assumption that all individuals use the same or very close to the same set of importance weights (logit coefficients) is often questionable. Hauser and Urban (1977) suggest grouping individuals into homogeneous preference segments *prior* to parameter estimation as one method of realistically dealing with the homogeneous assumption. Thus, each population for which a set of parameters is estimated is defined as a set (segment) of individuals for which it is reasonable to expect homogeneity with respect to the estimated parameters. This is the approach used.

5. Methodology

The methodology proposed uses segmentation to obtain relatively homogeneous segments of decision makers, estimates the parameters for the logit model for each segment, calculates the choice probabilities for each individual in the segment using these parameters, and finally determines if the differences among the probabilities of choosing various suppliers are statistically significant.

The multinomial logit model will be the basic mechanism used in implementing the desired segmentation scheme. The logit model estimates for each individual the individual's probability of selecting each of the alternatives in the choice set. Consider two individuals, designated as individual 1 and individual 2. Assume for individual 1 the logit model estimates the following choice probabilities for three suppliers: 90% for supplier A, 5% for supplier B, and 5% for supplier C. For individual 2 the estimated probabilities are 40% for supplier A, 30% for B, and 30% for C. If one were asked to predict which supplier individuals 1 and 2 would select, the maximum probability indicates supplier A is "most likely" for each individual. However, is it really correct to classify individual 2 as a supplier A customer, when there is a 60% probability he will not select supplier A?

There exists a considerable body of both empirical and theoretical literature which argues that when the probabilities are close it may be misleading to simply assign "close" probabilities to the highest alternative. The experimental psychology literature recognizes the sensory threshold concept. In organization theory Simon (1957) postulates that a "satisficer" will continue to pick his current alternative until another alternative becomes "sufficiently more attractive." Classical economists have recognized regions of indifference in dealing with utility concepts. Luce (1959) in developing an algebraic structure of choice models from the viewpoint of a mathematical psychologist spends considerable time and attention in dealing with "noticeable" differences.

The supplier loyalty segmentation scheme proposed in this article is based on the concept of statistically testing the significance of the differences in an individual's choice probabilities. Since the multinomial multiattribute logit model will be used to generate the individual's choice probabilities, one must understand how the logit probabilities are derived in order to evaluate the reasonableness of the segmentation method proposed. The logit model is based upon the assumption that an individual decision maker's overall preference for a choice alternative is a function of the perceived relative utility the alternative holds for the individual. The utility function is assumed to be separable into two components: (1) a deterministic component which is generally measured in terms of perceived values associated with the attributes of the alternative, and (2) an unobserved random component having a Weibull (Gnedenko extreme value) distribution, for which Gumbel (1954) has shown the random error term to be independent and identically distributed across all individuals.

Utility is thus written

$$U_i^k = D_i^k + \epsilon_i^k \qquad \text{where} \tag{1}$$

U_i^k = the utility of alternative k to individual i,
D_i^k = the deterministic component,
ϵ_i^k = the random component.

Luce and Suppes (1965) have shown that if the random component of a probabilistic choice model is independent and identically distributed, then the probability that an alternative will be chosen from a set of alternatives depends *only* on the deterministic component of the utility function, thus logit is a strict utility model. The probability that individual i will prefer alternative k from a set of available alternatives A_i, denoted by $P_i(k : A_i)$, is written

$$P_i(k : A_i) = \exp(D_i^k) \Big/ \sum_{l \in A_i} \exp(D_i^l). \tag{2}$$

While it is possible to have a nonlinear functional form for the deterministic component, the generally used form is linear and additive in terms of the attribute scores:

$$D_i^k = \sum_{j=1}^{J} a_j x_{ij}^k \qquad \text{where} \tag{3}$$

a_j = utility weight reflecting the importance of the jth attribute.
x_{ij}^k = score given by individual i to the kth alternative on the jth attribute.

It is also possible to have unique attributes pertaining to a specific alternative and a dummy variable representing an overall alternative influence defined in the deterministic component of the utility for an alternative. The logit function is essentially an estimate of the a_j weights in equation (3). The a_j parameters in the logit model are then the weight for each attribute that will be used across all k alternatives. The a_j parameters are thus importance weights. The variance associated with the above function can be computed directly from the data set used to derive the function. Knowledge of the variance enables one to determine whether or not the difference in the deterministic component scores of two alternatives is statistically significant at various confidence intervals. Estimating the statistical significance of the difference in the deterministic score components is equivalent to estimating the significance of the difference in the choice probabilities. Let D_{1i} be the true deterministic component score of alternative one for the ith individual:

$$D_{1i} = \mathbf{X}^{1i}\mathbf{A} \qquad \text{where} \tag{4}$$

$\mathbf{X}^{1i}$ = a $1 \times n$ vector of the ith individual's ratings of the attributes associated with alternative 1.

$\mathbf{A}$ = an $n \times 1$ vector of coefficients.

The estimated value of D_{1i} is then given by $\hat{D}_{1i}$:

$$\hat{D}_{1i} = \mathbf{X}^{1i}\hat{\mathbf{A}} \qquad \text{where} \tag{5}$$

$\hat{\mathbf{A}}$ = now an $n \times 1$ vector of coefficients estimated by the logit model from the sample data. The Maximum Likelihood Estimates of $\hat{\mathbf{A}}$ as used in logit have been shown to be consistent asymptotically efficient, and unique by McFadden (1976). The variance of $\hat{D}_{1i}$ denoted as $V(\hat{D}_{1i})$ can be calculated directly from the sample data:

$$V(\hat{D}_{1i}) = \mathbf{X}^{1i}\left[\sigma^2(\hat{\mathbf{A}})\right]\mathbf{X}^{1i} \qquad \text{where} \tag{6}$$

$[\sigma^2(\hat{\mathbf{A}})]$ = the variance-covariance matrix of $\hat{\mathbf{A}}$.

Since the deterministic component value for each of the k alternatives is a linear function of the same **A** vector of parameters, the variance associated with the difference between two deterministic components $(\hat{D}_{1t} - \hat{D}_{2t})$ would be

$$V(\hat{D}_{1t} - \hat{D}_{2t}) = (X^{1t} - X^{2t})[\sigma^2(\hat{\mathbf{A}})](\mathbf{X}^{1t} - \mathbf{X}^{2t}). \tag{7}$$

Assume that for a given individual the estimated probability associated with alternative one is higher than the estimated probability associated with alternative two. The question we wish to address is how significant is this difference. At the 95% confidence level the test of the null hypothesis (no difference) would be as follows:

$$H_0 : D_{1t} \leqslant D_{2t} \qquad \text{Do not reject } H_0 \text{ if } z \leqslant 1.65,$$
$$H_1 : D_{1t} > D_{2t} \qquad \text{Reject } H_0 \text{ if } z > 1.65, \qquad \text{where}$$

$$z = \frac{\hat{D}_{1t} - \hat{D}_{2t}}{\sqrt{V(\hat{D}_{1t} - \hat{D}_{2t})}}.$$

Because the random error terms in the logit model are assumed to be independent and identically distributed (i.i.d.), the above binary choice model may be extended to include more than two alternatives. One could estimate the significance of the pairwise differences between the first and second rated alternatives, first and third, and the second and third using the above approach.

The behavioral logic underlying this approach is rather straightforward. Individuals who perceive large differences in the attribute values between alternatives have a stronger relative preference for the highest rated alternative. They are less likely to switch to the second rated alternative, and are more likely to have a statistically significant difference in the deterministic component of the utilities of the alternatives. Conversely individuals whose attribute perceptions of the alternatives do not have a strong preference for the first rated alternative relative to the others are more susceptible and open to inducements to switch. This methodology will be implemented on the following survey data.

6. Data

An initial pretest questionnaire asked electrical equipment purchasers to rate the importance of 21 product and service attributes (i.e. short circuit strength, maintenance requirements, and warranty) and then to rate the major suppliers in the industry on a poor to good scale on each attribute. The pretest generated 98 responses. The responses were factor analyzed and a set of nine important and relatively independent attributes that influence the purchase of electrical equipment were identified.[1]

[1] It is not possible to list the specific attributes without revealing proprietary information. The firm involved has spent considerable time and effort on developing the original list of 21 attributes. A number of the attributes (price, appearance of product, warranty, quality, availability of spare parts, maintenance requirements, ease of installation, reliability, energy losses, short circuit strength, meets delivery dates, financial strength, quality of salesmen, research and development capability, and geographic location of supplier) are rather standard attributes which should be well known to competitive suppliers. However, the firm believes they have identified other attributes not commonly considered by competitors. A number of these nonstandard attributes are in the set of nine attributes related to choice. To indicate these attributes and the standard attributes that seem to underlie supplier rankings would reveal to competitors dimensions and relationships they do not seem to be currently aware of.

In the next section the total market is divided into 12 segments in which the membership within each segment is very homogeneous with respect to the logit coefficients for the nine attributes related to choice. To reveal this information would inform competitive suppliers how this firm perceives segments in the marketplace and within each segment the attributes the firm will be stressing.

Because of the obvious proprietary nature of the attribute names and the fact readers do not need this information in order to apply the process described in this article to their own data set, the nine key attributes will not be identified by name.

Basic mailing lists of individuals at utilities, REC's, municipalities, and industrial firms who were decision makers in the purchase of electrical equipment were purchased from two separate trade publications. These lists were merged and supplemented by the company salesforce. A final list of over 7,000 names and addresses was generated. A nationally respected market research firm was employed to administer the mail questionnaire. Each respondent received a pre-questionnaire letter indicating that he would be receiving a questionnaire a week to 10 days following this letter. It asked him for 15 minutes of his time to give guidance to an electrical supplier who wished to best fit its product and service attributes to the needs and wants of the customers.

Respondents were asked to rate the relative importance of nine product and service attributes in determining the purchase of a specific type of electrical equipment. The respondent also provided his current perception of each supplier known to him using a good to poor scale on each of the attributes per supplier. Respondents were asked to give an overall rating of each supplier and indicate from which supplier they had purchased a particular type of equipment the last time they purchased it. Other sections of the questionnaire included demographics of the firm, and the customer's interest in some specific product modifications and new product concepts. The entire mailing list received a questionnaire and the overall response rate was over 40%. A follow-up phone check of nonrespondents failed to detect any significant nonresponse bias.

7. Analysis

A preference index for each major supplier was computed per respondent. Respondents provided an *overall evaluation* of each supplier on a line continuum from good to poor. This was calibrated from 50 (good) to 1 (poor) providing a 50-point base preference scale. Points were added to the base preference scale for respondents who indicated they intended to make a purchase within the coming year and that they had a strong preference for the given supplier. In order to incorporate influence from actual behavior, points were also added to this scale if the respondent's last purchase was from the given supplier, the number of points added decreased in relation to the number of years elapsed, since the purchase. The adjusted base preference scale (after points are added) is referred to as the individual's preference index.

The preference index combines information on both the stated intentions and actual prior behavior of customers toward suppliers. This preference index is then used to provide the ranking of the suppliers required to calibrate the logit model. The probability of purchasing from a given supplier is assumed to be in relation to the customer's relative preference for the given supplier. Recall that the logit model requires a ranking of the alternatives (suppliers) as the dependent variable input. The nine attributes identified in the pretest as important and relatively independent are the nine independent variables.

A logit function could now be calibrated for the total population of customers. Then using the *one* set of logit coefficients the individual probabilities of purchasing from each supplier could be computed for each respondent. This would be appropriate if one believes the population is homogeneous with respect to the logit coefficients. Here the logit coefficient represents the relative importance of a given attribute in determining preference. The marketing staff of the firm strongly felt that there were segments of customers with very different weightings of attributes in their preference function. Behaviorally this meant that while the firm considered all the small REC's in the South to be homogeneous in their perceptions of the relative importance of such attributes as price, installation, maintenance, energy losses, etc., this group is very different from the large utility companies located in the Northeast, both in terms of what attributes are most important and how the major suppliers are perceived. Reasons for these differences between segments relate to differences in technical sophistication of the various customers, different sales force call patterns, and different promotional efforts. For example, a large utility with a sophisticated engineering staff will place different values on product features, initial price, and support services offered by the supplier than a small REC with no engineering staff and little technical sophistication. Given that the assumption of homogeneity with respect to one set of logit coefficients was believed to be unrealistic, an attempt was made to segment the customers into groups that were reasonably homogeneous with respect to the given set of logit coefficients. *A priori* the marketing staff indicated three main dimensions underlying heterogeneity. Therefore respondents were initially segmented on these dimensions: geographic area, type of customer, and size. In this industry, size of the customer is measured in terms of the number of meters served. There were four geographic regions, four types of customers, utilities were split into three size groups in terms of meters served, the REC's and municipals were split into two size groups and industrials were not split on size. This produced 12 utility segments, 8 REC segments, 8 municipal segments, and 4 industrial segments for a total of 32 *a priori* segments to be considered.

Logit models were run on each segment. Adjacent segments (segments with two common dimensions) i.e. a segment of small REC's located in the Southeast and a segment of small REC's located in the Southwest were combined if the differences in the set of logit coefficients were not significant at the 0.05 level. See Appendix 1 for an example of how the significance in sets of logit coefficients is computed. After all adjacent combinations had been accomplished, the number of segments had been reduced to ten. The homogeneity with respect to the logit coefficients within each of the remaining segments was then tested. Each remaining segment was randomly split into two subsamples and a logit model run on each subsample, then the two sets of logit coefficients were compared to see if differences between the sets were significant at the 0.05 level using the same procedures described in Appendix 1. If the differences were not found to be significant, another random subsample was selected and the process repeated. If three successive sets of subsamples did not have significant differences in their sets of logit coefficients, the process was terminated and the segment was viewed to be relatively homogeneous with respect to the logit coefficients. Since the logit coefficients indicate the importance of the various attributes influencing the probability of purchase, the behavioral interpretation of a homogeneous segment is that members of that segment use relatively the same preference function in selecting a supplier.

If the difference between sets of logit coefficients was significant, the segment was examined in an attempt to identify dimensions responsible for the heterogeneity; for example, it may be that the preference functions of small REC's varied in relation to the number of outside consultants they used. Heterogeneous segments were then split on dimensions that appeared to be related to systematic differences in the logit coefficients. Newly formed segments were again tested for adjacent combinations and then for internal homogeneity with respect to the logit coefficients. Eventually 12 segments were identified and segment sample sizes ranged from a low of 148 to a high of 464. Each segment was analyzed separately producing 12 different logit models. The respondents were quite homogeneous within a segment, and there were some very significant differences in logit functions between segments.

Then using the appropriate logit function for each respondent, the respondent's probability of purchasing from each major supplier was computed. These individual probabilities were analyzed in terms of the significance of the differences using the methodology previously described. The particular statistical confidence level (95%) used in this paper as a measure of significant differences in probabilities is a situationally specific judgment made by the researcher. In practice the chosen level will vary from one situation to another depending upon such considerations as the relative costs of Type I and Type II errors.

Four groups of customers were identified based upon this analysis: our loyal customers, competitive customers, switchable customers, and competitor's loyal customers. The segment labeled *our loyal customers* is defined as that segment in which our firm is currently perceived as vastly superior to all competitors. The loyal customer has a very high probability of purchasing his next transformer from our firm. This segment consists of respondents whose probability of purchasing from our firm is highest and is significantly (at the 0.05 level) above the second highest probability. The *competitive* segment consists of customers who have a slight preference for our firm over other suppliers. These are respondents whose probability of purchasing from our firm is highest, but the differences between the highest probability and one or more of the other probabilities is not statistically significant at the 0.05 level. The *switchable* group consisted of respondents whose probability of purchasing from one or more other suppliers is higher than their probability of purchasing from our firm but the difference between the probability of purchasing from our firm and the firm with the highest probability is not statistically significant. This customer's first preference is for a competitor but perceives our firm as relatively close to his first choice. The *competitor loyal* group consists of respondents whose probability of purchasing from one or more of the competitors is higher than the probability of purchasing from our firm and the difference in these probabilities is statistically significant. It is unlikely that members of this segment will purchase their next transformer from our firm.

8. Implementing the Analysis

Our firm has divided the US market into three geographic sectors, each of which has a district manager who is in charge of a sales and promotion budget. The key to getting any new methodology, especially methodology employing advanced statistical or mathematical programming, adopted is to first make sure the managers who must implement the methodology fully understand the methodology, and, second, actually believe it will be an improvement on the status quo. I was unable to persuade all three managers to use the methodology described in this article and concentrate their marketing resources on the customers who did not have strong supplier loyalties. Two of these managers were responsive to the choice modeling approach and derived the following strategy. They cut back on the general promotional advertising in trade journals and reduced the call pattern over all customers by the field sales force. With the money and personnel they saved they formed a "missionary" sales force to operate out of district headquarters.

The strategy developed by these two managers was to concentrate on the "competitive" and "switchable" groups in their territories. They used considerable direct mail supported by the "missionary" sales force. The direct mail attempted to emphasize the particular attributes and products of greatest interest to the particular customer. Which attributes and products to emphasize was indicated by the logit analysis on the particular segment to which the respondent belonged. The "missionary" sales force also emphasized the particular attributes and products identified by the logit analysis as most salient and of most interest to respondents of a particular segment. Simply stated, the strategy of these two managers is to reduce the marketing effort to both our and the competitor's brand loyal segments and to expand the marketing effort on those consumers for whom our firm is competitive. This strategy is based upon the belief that it is within the "competitive" and "switchable" groups of customers that changes in market share are most likely. While the *services* provided to provided to the firm's brand loyal customers were not reduced, the repetition of the same message was reduced. The marketing effort to other firms' brand loyal customers has been substantially reduced.

The third district manager, who was older, had spent his entire career in sales, and had a very limited background in statistics and modeling, did not feel comfortable with the modeling approach. He chose to continue to use the existing marketing strategy.

After a full year of implementing the various marketing strategies, the following results occurred. First, total industry sales were down 15%, total industrial sales appeared to be down in all three districts, with the decline in district two above that of the other two districts. Our sales in the two districts using the choice model segmentation approach were up 18% and 12%. Our sales in the third territory were down 10%.

Table 1 presents the change in sales per group of customers by sales district. Districts One and Two used the choice modeling segmentation strategy while District Three used the existing approach.

Sales are measured in terms of awarded contracts rather than shipments. It is clear that major increases in the first two districts occurred because of substantial increases in the "competitive" segment supported by increases in the "switchable" group.

In the year preceding the above data the industry sales were down about 8% from the previous year and the district sales were: district one (+2%), district two (−7%), and district three (−3%). Thus it does not appear that the results in Table 1 are to be explained principally as a function of different sales trend lines in the different sales districts.

In an attempt to obtain some estimate of what sales might have been if the supplier segmentation approach had not been implemented, the total sales in each of the 12 customer segments were multiplied by the aggregate choice probabilities estimated by the logit function for that segment. This approach produced the following estimates of sales results for our three districts: District One (−9%), District Two (−8%), and District Three (−11%).

The results are certainly supportive of the choice modeling segmentation approach, but they are not conclusive. First, one must recognize that one year is not a complete purchase cycle for many customers; thus data over more than one year are required. While sales data will continue to accumulate, the experimental design situation in which one district does not use the new approach will not continue. Based upon the marketing experience gained in the last year, the president of the firm has ordered increased implementation of the choice segmentation approach, particularly with respect to new product introductions in all districts. All three districts are now using this approach.

A second argument that should be considered is that perhaps the sales increase was due to use of direct mail and a "missionary" sales force and this marketing approach

TABLE 1

Annual Change in Sales by District, by Consumer Group

	District		
Consumer Group	One	Two	Three
Our Brand Loyal	+ 2%	+ 3%	+ 3%
Competitive	+ 26%	+ 18%	− 9%
Switchable	+ 16%	+ 8%	− 18%
Competitors' Brand Loyal	− 4%	− 3%	− 4%
Total	+ 18%	+ 12%	− 10%

would in itself have increased sales independent of any choice modeling. The problem is that in marketing systems many variables are interacting. It is difficult to assign results directly to one component of an interactive system. Some additional information may be generated on this issue in the next year as some "missionary" sales force and direct mail are targeted for competitive loyal customers in two of the twelve segments. It is felt that a new product the firm is introducing so strongly dominates other existing products on the salient attributes of these two segments that perhaps even some competitor loyal customers may be converted to the new product.

Finally, there is an issue seldom directly addressed in quantitative articles proposing new methodology. Do the more complex methods proposed have real advantages over simpler less difficult methods of making the same decision? For example, couldn't one simply ask customers to rank the suppliers and then concentrate on all the customers who rank our firm second? This would provide a target group for the direct mail and "missionary" sales force without using the extended logit model.

Since I believe this is an issue with practical management implications that should be addressed in articles suggesting use of new or sophisticated methodology, this issue will be considered in some detail. Perceptions concerning suppliers are generally obtained on a rank or interval scale. Consider first the rank order scale, to go after all customers who rank our firm second or some close variation of this scheme. First this approach would ignore the competitive segment and the possibility that some of the customers ranking our firm third or even fourth are switchable. More important this ignores the crux of our problem, which is the significance of the difference in preference between the first and subsequent choices. Empirically, 52% of the customers who ranked our firm second or tied for second were classified in the competition's loyal segment. Empirically the use of simple rank order data can produce very different segments and conceptually does not deal with the significance of the differences in choice probabilities that is addressed by the modified choice-model approach.

Next consider an interval scale of preference such as the preference scale used in the above case example. Consider two sets of ratings for the four suppliers: A is $(40, 35, 32, 28)$ and B is $(40, 33, 15, 10)$. In which of these cases is the second choice competitive with the first? The problem is that individual scaling differences as well as true perception differences are involved. In order to establish critical values in terms of differences between first and subsequent choices the data must be aggregated. Should one standardize the individual ratings prior to aggregation or not? In the nonstandardized form the second choice in A (5 units difference) may be competitive while in B (7 units difference) the second choice may not be competitive. Using standardized ratings, the difference between first and second choice in B is smaller than the difference in A, producing just the opposite results. The theory as to why either of the above approaches realistically measures the significance of perceptual differences is unclear. Without such a theory how can one have any confidence in either process?

One cannot make a normative judgment as to which approach is preferable unless one can derive an underlying behavioral theory that supports one of the above approaches. Theil (1970) and McFadden (1973) derive the logit approach, in terms of an underlying rational behavioral theory, that deals directly with the above problem of estimating individual measures of preference from sample statistics. The approach used in this article simply extends the behavioral theory underlying the logit approach.

Practically, it should be recognized that logit computer programs have been widely disseminated in the marketing research community and are generally available. The extensions, which are detailed in this article, are rather easy modifications for an experienced programmer to make on the basic logit program. Thus to this author the cost of 15–30 minutes of programmer's time and some test runs really is not a significant barrier to use.

Thus when one considers the dollars spent on generating good survey data and the potential profits involved in successfully implementing a marketing strategy based on measuring supplier loyalty it makes little sense to use a segmentation scheme that lacks a strong underlying rationale simply because it is computationally easier to compute and implement.

9. Conclusion

Supplier loyalty, the current relative strength of customer preference for a given supplier, is a key dimension to consider in allocating marketing effort. This article indicates a practical method for obtaining measurement on this dimension for durable goods and many large ticket industrial products which have long purchase cycles. The particular assumptions underlying the logit choice model allow one to extend the logit model to look at the statistical significance of the individual choice probabilities. This methodology produced a means of segmenting the total market on the current brand loyal dimension. The resulting segmentation served as the basis for a marketing allocation strategy that produced impressive sales results.

Appendix 1

A standard criterion for goodness-of-fit for statistical models estimated by maximum likelihood is the log likelihood function evaluated at the estimated parameters. In symbols,

$$L = \sum_{n=1}^{N} \sum_{i=1}^{J} S_{in} \log P(i \mid x^n, \hat{b}) \qquad \text{where}$$

L = the log likelihood function to be maximized,
N = number of individuals in the sample,
J = number of alternatives,
S_{in} = a 0-1 variable, for each individual S_{in} is one for the chosen alternative and zero for all other alternatives,
x^n = vector of the attribute values estimated by the nth individual,
$\hat{b}$ = estimated parameters,
$\log P(i \mid x^n, \hat{b})$ = log of the probability of individual n selecting alternative i, given x^n and $\hat{b}$.

This function is maximized by b coefficients that are the maximum likelihood estimates. Note that this function deals with the log of a probability and recall that for any probability less than one the characteristic of the log is negative. Thus, the *maximum* value of the log likelihood function for a perfect fit, i.e., a probability of one for the selected alternative and zero for all others, would be *zero*.

The log likelihood function can be used in statistical "likelihood ratio" tests allowing one to statistically compare the fits of various logit models on the same data set. The statistic $2\log\lambda$, where λ is the ratio of likelihoods, is commonly used to compare goodness-of-fit logit models. The statistic is asymptotically distributed as chi square with v degrees of freedom (Rao 1973, p. 419). Here, v is equal to $n - s$, where n is the sample size and s is the number of parameters estimated in the function.

Consider the following example; say we randomly split a sample of 400 individuals into two subsets of 200 each and calibrate a logit model on the same nine attributes for each segment. The two sets of coefficients are as follows:

Attribute	Logit Coefficients Segment One	Logit Coefficients Segment Two
1. Price	0.11	0.04
2. Appearance of Product	0.11	0.10
3. Warranty	0.59	0.24
4. Quality	0.06	−0.04
5. Availability of Spare Parts	0.09	0.03
6. Maintenance Requirements	0.11	0.04
7. Ease of Installation	0.54	−0.01
8. Reliability	0.36	0.04
9. Energy Losses	0.45	0.10
Log Likelihood	− 33.23	− 138.58

Are the differences in the coefficients indicative of different value systems used by the two groups in relating the attributes to preference or are these differences simply due to sampling?

For log functions the "likelihood ratio" is 2[log(1) − log(2)] which in our case is 2[138.58–33.23] or 210.70. Using the standard chi square table one observes that 210.70 for 191 d.f. indicates the difference in coefficients of this magnitude will occur less than one time in a thousand by chance alone. Thus since we are using 0.05 as our critical value we would conclude that the two subsamples are significantly different and not homogeneous with respect to the logit coefficient.[2]

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References

Batsell, Richard R. and Leonard M. Lodish (1981), "A Model and Measurement Methodology for Predicting Individual Consumer Choice," *Journal of Marketing Research*, 18 (February), 1–12.

Blattberg, Robert C. and Subrata K. Sen (1976), "Market Segments and Stochastic Brand Choice Models," *Journal of Marketing Research*, 13 (February), 34–45.

Choffray, Jean-Marie and Gary Lilien (1978), "A New Approach to Industrial Market Segmentation," *Sloan Management Review*, (Spring), 17–29.

Currim, Imran S. (1981), "Using Segmentation Approaches for Better Prediction and Understanding from Consumer Model Choice Models," *Journal of Marketing Reseach*, 18 (August), 301–309.

Czepiel, John A. (1974), "Word-of-Mouth Processes in the Diffusion of a Major Technological Innovation," *Journal of Marketing Research*, 11 (May), 172–180.

Doyle, Peter (1977), "An Application of Probit, Logit, and Tobit in Marketing: A Review," *Journal of Business Research*, 5 (September), 235–248.

Flath, David and E. W. Leonard (1979), "A Comparison of Two Logit Models in the Analysis of Qualitative Marketing Data," *Journal of Marketing Research*, 16 (November), 533–538.

Frank, Ronald E. (1967), "Correlates of Buying Behavior for Grocery Products," *Journal of Marketing*, 31 (October), 48–53.

Gensch, Dennis H. and Wilfred Recker (1979), "The Multinomial Multi-Attribute Logit Choice Model," *Journal of Marketing Research*, 16 (February), 124–132.

Green, Paul A. (1978), "An AID/Logit Procedure for Analyzing Large Multiway Contingency Tables," *Journal of Marketing Research*, 15 (February), 132–136.

Gumbel, E. J. (1954), "Statistical Theory of Extreme Values and Some Practical Applications," *National Bureau of Standards Applied Mathematics, Series* 20, 33.

Hauser, John R. and Glen L. Urban (1977), "A Normative Methodology for Modeling Consumer Response to Innovation," *Operations Research*, 25 (July–August), 579–619.

Hayward, George (1972), "Diffusion of Innovation in the Flour Milling Industry," *European Journal of Marketing*, 6 (Autumn), 195–202.

Kuehn, Alfred A. (1962), "Consumer Brand Choice as a Learning Process," *Journal of Advertising Research*, 2, 4 (December), 10–17.

Luce, R. Duncan (1959), *Individual Choice Behavior: A Theoretical Analysis*, New York: John Wiley & Sons, Inc.

——— and P. Suppes (1965), "Preference, Utility, and Subjective Probability," in R. D. Luce, R. R. Buch and E. Galanter, eds., *Handbook of Mathematical Psychology*, 3, New York: Wiley, 249–410.

McFadden, Daniel (1976), "The Theory and Practice of Disaggregate Demand for Various Modes of Urban Transportation," Paper presented at Seminar on Emerging Transportation Planning Methods, Daytona Beach, Florida, (December).

——— (1973), "Conditional Logit Analysis of Qualitative Choice Behavior," in Paul Zarembka, ed., *Frontiers in Economics*, New York: Academic Press.

Punj, Girish N. and Richard Staelin (1978), "The Choice Process for Graduate Business Schools," *Journal of Marketing Research*, 15 (November), 588–598.

Rao, C. R. (1973), *Linear Statistical Inference and Its Applications*, 2nd Edition, New York: John Wiley & Sons.

Rao, Vithala and F. W. Winter (1978), "An Application of the Multivariate Probit Model to Marketing Segmentation and Product Design," *Journal of Marketing Research*, 15 (August), 361–368.

Robertson, Thomas S. and Yoram Wind (1980), "Organization Psychographics and Innovations," *Journal of Consumer Research*, 7 (June), 24–31.

Spekman, Robert E. (1981), "Segmenting Buyers in Different Types of Organizations," *Industrial Marketing Management*, 10 (February), 43–48.

——— and Louis W. Stern (1979), "Environmental Uncertainty and Buying Group Structure: An Empirical Investigation," *Journal of Marketing*, 43 (Spring), 54–64.

Simon, H. (1957), *Models of Man*, Wiley: New York.

Theil, Henri (1970), "On the Estimation of Relationships Involving Qualitative Variables," *American Journal of Sociology*, 76, 103–154.

Thomas, Robert J. and Yoram Wind (1981), "Toward Empirical Generalizations on Industrial Market Segmentation," in *Industrial Marketing: A View to the Future*, Spekman and Wilson, eds., Chicago: American Marketing Association.

Wind, Yoram (1970), "Industrial Source Loyalty," *Journal of Marketing Research*, 7 (November), 450–457.

——— (1978), "Organizational Buying Behavior," *Review of Marketing*, Zaltman and Bonoma, eds., Chicago: American Marketing Association, 160–193.