CHOICE-BASED SEGMENTATION AND TARGETING THE "SWITCHABLE" CUSTOMER

MARK YOUNG, Winona State University

Choice-based market segmentation forms the basis for identifying customers who have choice probabilities that indicate they may be prone to switching suppliers. Marketing strategies are developed based on logit coefficients to target this "switchable" market segment. An overview of multinomial logit choice modeling along with a description of coefficient estimation with SPSS's survival analysis maximum likelihood function are provided and then illustrated with data from the auto machine shop suppliers industry.

INTRODUCTION

Market segmentation is one of the first steps in the strategic marketing process and should serve as a key element in corporate strategy. It recognizes that buyers in any market may differ in their response to marketing mix variables. The managerial presumption is that: if these *response differences* exist, can be *identified*, remain reasonably *stable* overtime, and the segments can be efficiently *reached*, the firm may increase its sales and profits beyond those obtained by assuming market homogeneity (Green, Tull and Albaum 1988). The process of segmenting is the link between the buyers' needs and the company's marketing offer.

Today, more than ever, information is critical for effective business operations and the technologies for collecting, processing, and disseminating market information are expanding exponentially. Increasingly, companies are utilizing this information through interactive marketing systems which track and link measurable outcomes to marketing efforts that guide decision making (Marshall 1996). Future sales of low involvement, routinely purchased consumer goods and straight rebuy industrial goods may be readily predicted from past purchase behavior (Gross and Peterson 1983). However, consumer purchases that involve extensive or limited problem solving or industrial situations involving new or modified rebuy purchases are better predicted as a function of product attributes and supplier services (Gensch 1987). A segmentation methodology that is well suited for predicting the probability of purchase, based on a set of product attributes, supplier services and behavioral response variables, is choice-based segmentation.

Choice-based segmentation is an analysis typically conducted at the individual buyer level and relates a buyer's likelihood of selecting a particular supplier/brand to various factors affecting choice of supplier/brand. Gensch (1984) developed a segmentation methodology that examines differences in choice probabilities to classify buyers into segments based on their likelihood of switching suppliers. Understanding the choice criteria utilized by buyers in selecting their supplier/brand can help in targeting buyers that have the highest probability of becoming customers and can provide insight into redesigning and/or repositioning the company's offer to better meet the targeted customers' needs. A multinomial logit, discrete choice model is used to estimate the probability that a buyer would choose a particular supplier/brand. Targeted buyers are referred to as "switchable" and have choice probabilities that are slightly higher or lower of selecting a particular supplier/brand as compared to their next most preferred supplier/brand. Buyers that have a high probability of selecting a particular supplier/brand and very low probability of selecting alternative suppliers/brands are considered "non-switchable" and are not targeted.

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This article provides a brief overview of the multinomial logit choice model, describes how the coefficients may be estimated using readily available SPSS or SAS software, presents a supplier preference segmentation scheme based on the model's coefficients, and illustrates the technique with an auto machine shop supplier example.

CHOICE MODELING

Early marketing studies have relied on the multinomial logit model for new product strategy (Hauser and Urban 1977; Kim, Srivastava, Han 2001), store choice (Guadagni and Little 1983), promotion effects (Bronnenberg and Wathieu 1996), price effects (Krishnamurthi and Raj 1991), consumer sales response (Bucklin 1998) and other consumer behavioral issues. Buyer behavior consisting of a single selection (brand/supplier) from a finite set of alternatives can be described with a discrete choice model. Discrete choice models map indices of observable product/service attractiveness characteristics to choice preferences as a deterministic component. Since not all factors affecting choice can be included in the indices, a stochastic (random) component representing unobserved attributes, measurement errors, and functional misspecification is added to the deterministic component in the model. Assumptions implied about the nature of the stochastic component create a variety of discrete choice models. Baltas and Doyle (2001) provide a comprehensive review and taxonomy of choice models based on the models' treatment of the stochastic components.

The multinomial logit model used in this paper assumes the random terms to be independently identically distributed, meaning they have the same distribution, with the same means and variances and are uncorrelated within and among individuals. This simplistic assumption implies that an improvement in one alternative's utility will have a proportionally equal reduction in the preference for each of the other choices. Whereas other variations of the discrete choice model can overcome this restriction, they add complexity and estimation difficulties that may provide marginal practical value for this application. Luce and Suppes (1965) have shown that when the independently identically distributed assumption is accepted, the choice probability depends only on the deterministic component and can be expressed as in Equation 1. The logit model estimates, for each buyer, the buyer's probability of selecting each of the alternatives in the choice set of suppliers/brands. The probability that buyer i will select supplier/brand j from a set of available suppliers/brands J, denoted by

$$P_{ij} = e^{Aij} \Big/ \sum_{j \in J} e^{Aij} \tag{1}$$

P_{ij} = the probability that buyer i will choose supplier/brand j;

A_{ij} = attractiveness of supplier/brand j to buyer i; = $\sum w_k b_{ijk}$;

$_{ijk}$ = the value of variable k (influences on choice)for supplier/brand j when buyer i selected a supplier/brand;

w_k = derived importance weight associated with variable k; and

e = 2.718282.

Data used to create the choice model usually involves the buyer's most recent choice of supplier/brand, in addition to demographic, geographic, psychographic, and behavioral segmentation variables. Much of the data is typically found in existing customer databases; however, marketing research must often be conducted to update the database and collect additional information on competitor comparisons.

Model Estimation

Typically, specialized statistical software (e.g., NLOGIT) has to be used to estimate this type of disaggregate choice model. However, because the likelihood function of the multinomial logit model has the same form as a survival analysis model (Kuhfeld 1996), common software such as Statistical Package for the Social Sciences (Cox Regression) or SAS (Proportional Hazards Regression) can be utilized if the data is rearranged to be consistent with survival time data. The data set will have multiple rows of data for each respondent (a separate row for each alternative choice of supplier/brand). The SPSS Cox Regression example presented in Figure 1 illustrates an example where there are six suppliers to choose among, as indicated by six rows of data for each customer. The preferred choice of supplier is coded as 1, indicating it occurred in time period one, while nonchosen suppliers are coded as 2, indicating they occurred in later time periods in order to be consistent with survival analysis methodology. An additional variable (status) is a copy of the choice variable and is needed to handle censored data in this procedure. Censored cases are those for which the event (choice of supplier/brand) has not occurred. The covariates are the demographic, geographic, psychographic, and behavioral variables thought to influence choice (e.g., catalog, delivers, name, order, knowledge, competent, responsive) and the strata input box specifies the respondent identification.

Choice-Based Segmentation

The primary outputs of interest from the analysis are the logit coefficients and their significance. For predicting choice, all of the coefficients may be used in the model regardless of their significance, assuming they were justified before the model was estimated. However, examining the significance and the size of the coefficients (assuming same scales or variable standardization) one can develop an understanding of the primary drivers of choice. These choice drivers can then be used to develop marketing programs that maximally impact choice.

Individual choice probabilities for selecting each of the suppliers/brands can be computed based on this one set of coefficients by inputting the data into Equation 1. The choice probabilities for each individual will sum to 1. These probabilities form the basis for categorizing buyers into segments. Comparing the changes in the values of –2 times the log likelihood for different models (likelihood-ratio) is the basis for statistically comparing the fits of various logit models on the same data set estimated with the maximum likelihood function (see Appendix 1 for details). However, instead of making statistical comparisons among choices, an effective and simpler segmentation scheme based on managerially determined cutoffs for different classifications is to categorize buyers into predetermined segments such as: Loyal, Lost, and Switchable.

Loyal Segment (Loyal): Customers in this segment have a significantly higher probability of purchasing from the seller's company than the probability that they would buy from the next closest competitor. (e.g., probability of choosing seller's company/brand >.80)

Competitor Loyal Segment (Lost): Customers in this segment have a significantly lower probability of purchasing from the seller's company than from other suppliers/brands. Thus these customers are highly likely to buy only from a competitor and can be classified as lost customers. (e.g., probability of choosing seller's company <.15)

Switchable Segment (Switchable): Customers in this segment have a slightly higher or lower probability of purchasing from the seller's company than their next most preferred supplier/brand. (e.g., probability of choosing seller's company between .15 and .80)

Each buyer's choice probabilities are examined, allowing him/her to be classified as either "switchable", "loyal" or "lost". Table 1 provides examples of computed choice probabilities and the actual choice of supplier for two buyers. Buyer 1 would be classified as "lost" and not targeted with information from the seller's company because of this buyer's strong perception of the appropriateness of competitor C in meeting his or her needs. However, buyer 2 provides an example of a "switchable" buyer in that his or her chosen supplier has a choice probability that is moderate in comparison to the buyer's probability of selecting the seller's company. Buyers in the "switchable" segment can be targeted with information most relevant (based on the logit coefficients) to their choice through direct mail, e-mail, or other communications.

Does this segmentation methodology provide advantages over simply asking buyers to rank order their supplier/brand choices or to rate suppliers/brands? The selling company could then concentrate its efforts on the buyers who rank or rate their company high. The ranking procedure is lacking in its ability to discriminate among buyers who are very set in their choice from those who are reasonably undecided. In Table 1, company A would be ranked as the second choice for buyer 1; however, the probability of selecting company A is only 6.4 percent compared to their first choice (87.8 percent), which means there is

FIGURE 1
Model Estimation Utilizing SPSS Cox Regression Procedure

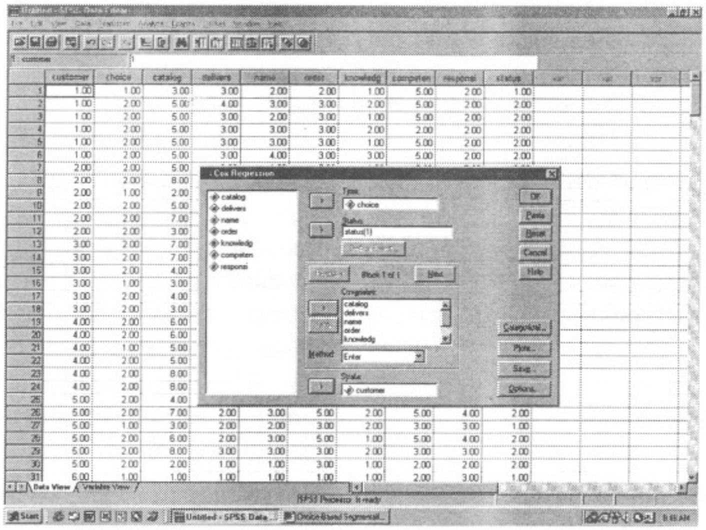


TABLE 1
Individual Choice Probabilities

	Choice Probabilities	
Supplier	**Buyer 1**	**Buyer 2**
Company A (seller's company)	6.4%	26.4%
Company B	1.6%	**47.6%
Company C	**87.8%	15.2%
Company D	4.2%	10.8%
**Selected Supplier		

little chance of converting this buyer. Whereas, the second place ranking of company A for buyer 2 has the opposite interpretation, and he or she would be targeted based on the moderate choice probability of his/her first choice. Rating data raises the issue of how individual buyers use scales differently. Should the data be standardized? If so, should this occur before or after the data is aggregated? Different results will occur with different processes of standardizing and aggregating the data. Unfortunately, there is no theory to guide these methods. However, the logit approach was derived from an underlying rational behavioral theory (McFadden 1973). Once this choice-based segmentation methodology and its computations are understood, its advantages over simpler and non-theory based methods become apparent.

Supplier Choice Example

The industry leader in the wholesale distribution of tools and shop supplies for engine rebuilders, Goodson Automotive Machine Shop Supplies, was experiencing a market share (see Figure 2) battle in a mature industry. Traditionally, Goodson successfully differentiated itself from the competitors with superior order fulfillment, knowledgeable salespersons, and outstanding catalogs displaying its broad product line. Goodson prided itself on its professionally created and produced catalog that rivaled high-end consumer catalogs in format and layout. Now other competitors seem to be closely monitoring Goodson's marketing practices and are quick to meet or beat their offers. Many of Goodson's service guarantees and policies are appearing in competitors' catalogs. In addition, two new competitors recently entered the industry offering low end pricing and no frills service. Instead of glossy, expensive to produce catalogs, the new competitors are offering newspaper quality product flyers that highlight featured products at discounted prices. The two new competitors do not have sales representatives and are strictly phone/mail order companies.

Success stories of Malcom Baldridge award winning companies that achieved their success by offering high quality products and services filled the business media; however, Goodson began to question if a high quality/high price strategy would survive in the auto shop supply industry. To help formulate a corporate strategy and to provide tactical marketing direction, Goodson decided to undertake marketing research to better understand their customers and competitors.

Goodson's existing database consisted of typical customer order related information such as names, addresses, sales volume, and order frequency. Management desired additional customer profile information (number of employees, primary service offered, type of organization, number of facilities, etc.), an evaluation of information sources for shop supplies (trade shows, trade magazines, sales people, sales literature, catalogs, etc.), and competitor evaluations on important choice attributes. Customers were *a priori* segmented based on eight geographical regions of the U.S. (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific) and five purchase volume categories (first time orders, annual orders < \$50, annual orders \$50 - \$1000, annual orders \$1000+, previous orders but none this year). A telephone interview survey was conducted with 600 randomly selected customers that proportionally fulfilled quotas in the above geographic and sales volume categories.

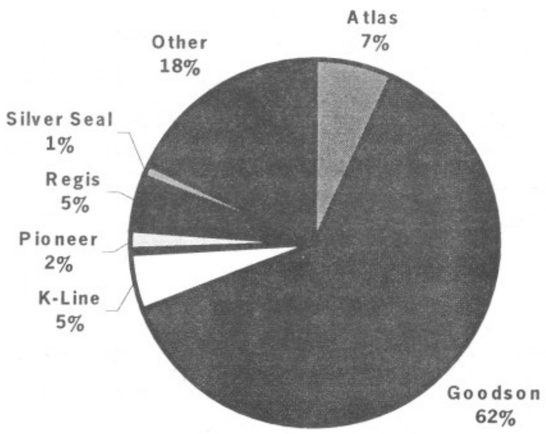
In-depth interviews with a convenience sample of machine shop supply buyers and discussions with Goodson's management led to the selection of seven factors that influence choice of supplier.

Provides a complete catalog.

- Delivers the order when promised.
- Carries brand name products.
- Gets your order right the first time.
- Has knowledgeable technical people you can call.
- Has competent sales representatives that call on you.
- Provides responsive customer service.

The six major auto shop suppliers (Atlas, Goodson, K-line, Pioneer, Regis and Silver Seal) were evaluated on the above choice attributes. In addition to these top six suppliers, many small regional suppliers exist and, when combined, hold approximately 18 percent market share. The small suppliers were identified but were not

FIGURE 2
Market Share: Automotive Machine Shop Suppliers



individually evaluated; only generic comments about purchasing from local suppliers were solicited.

The phone interviewers first had to identify and speak with the person that was most responsible for ordering shop supplies, which sometimes required several call backs to speak with the desired respondent. The questionnaire started by asking about the purchaser's usage and familiarity with different shop supply companies. The above seven factors thought to affect supplier choice where rated on a 10-point importance scale. Each of the six companies, with whom the respondent was familiar, was then rated on these seven factors also using 10-point scales. Respondents were then asked which companies' catalogs they currently had, which trade magazines they subscribed to, and which companies' sales representatives regularly called on them. The final section of the questionnaire involved classification type questions such as number of employees, services provided, future purchase intentions, etc. The interviewers did not reveal the research sponsor until after the interview in order to minimize interviewer bias.

A resulting data set of 582 usable responses that proportionally filled the geographic and purchase volume criteria was obtained. The following results are based on one of the categories with 50 respondents.

RESULTS

If there is reason to believe groups of buyers have different coefficients, then separate logit models should be computed for each subgroup or segment. Comparing the changes in the values of two times the log likelihood for different models (2[log(1) – log(2)]) is the basis for statistically comparing the fits of various logit models on the same data set estimated with the maximum likelihood function. The statistic is asymptotically distributed as a Chi-square with degrees of freedom equal to the sample size minus the number of parameters estimated in the model. In this example, it was assumed that the population of relevant buyers was homogeneous with respect to the logit coefficients within each of the *a priori* geographic and purchase volume categories. A separate set of coefficients was estimated for each of the *a priori* categories. Categories were combined if there was not a significant difference in their coefficients at the .05 level.

The coefficients for the discrete choice model were estimated with the Cox Regression procedure in SPSS and are presented in Table 2. Three of the seven variables have significant coefficients at the ten percent level of significance. The largest coefficient in Table 2 suggests that 'Provides a Complete Catalog' is a major influence in the selection of a supplier. The coefficients also suggest that the supplier must also 'Deliver the Order When Promised' and 'Get the Order Right the First Time'. More specific details about the supplier such as 'Carries Brand Name Products,' 'Has Knowledgeable Technical People When You Call,' 'Has Competent Sales Representatives,' and 'Provides Responsive Customer Service' were not statistically significant in this choice model. These estimated coefficients provide guidance in the development of marketing strategies and tactics to influence choice of supplier.

Figure 3's bar chart provides the average ratings for each of the seven importance factors based on the respondent's direct evaluations. Frequently, what customers say is important does not match what actually is important when they decide on suppliers. The choice model's coefficients estimate the importance of each factor in predicting choice in an indirect manner. Figure 3 indicates all the variables are important. This would be expected based on the rationale to include them on the questionnaire. However, not all of them may influence or determine choice. Some variables may be rated as important but all suppliers may be viewed as the same on this variable, which provides little assistance in utilizing this variable in strategy formulation. Some respondents may also be providing socially acceptable ratings or may not really know which factors influence them the most. Somewhat reassuring in this example is that the top three variables in the importance ratings are also the three significant variables in the choice model. Individual probabilities for selecting each of the six suppliers were then computed per buyer based on their group's one set of logit coefficients. Each buyer was placed in one of the three segments (Loyal, Lost, Switchable) based on their purchase probabilities.

Marketing strategies were designed that focused the resources on the "switchable" buyers and, in the above segment, emphasized a complete catalog, delivery on time, and getting the order right the first time. Some of the marketing effort was directed at communicating the company's superiority over the competition on the above three characteristics, however, the majority of the resources were directed at improving internal operations (bar coding, inventory management and order tracking) to ensure order fulfillment. The internal efforts provided customers with benefits they truly valued and which were less obvious and more difficult to copy by competition. More frequent catalog mailings and telemarketing efforts were directed at the "switchable" buyers while fewer mailings and no telemarketing was directed at the "Lost" segment. Whereas the company was unwilling to share objective results of their strategies, it does acknowledge positive outcomes and continue to utilize choice based segmentation in their decision-making processes.

CONCLUSION

Effective and efficient marketing typically begins with market segmentation. For consumer shopping goods or non-routine industrial buyer decisions, incorporating information about buyers' perceptions of alternative choices can facilitate segmenting the market into groups that vary in their likelihood of purchase. Targeting the "switchable" buyers by allocating resources and customizing the marketing messages based on the significant logit coefficients, formed the basis for developing marketing strategy for an industrial supplier. The choice-based multinomial logit segmentation methodology illustrated is practical to implement and can be estimated with common software.

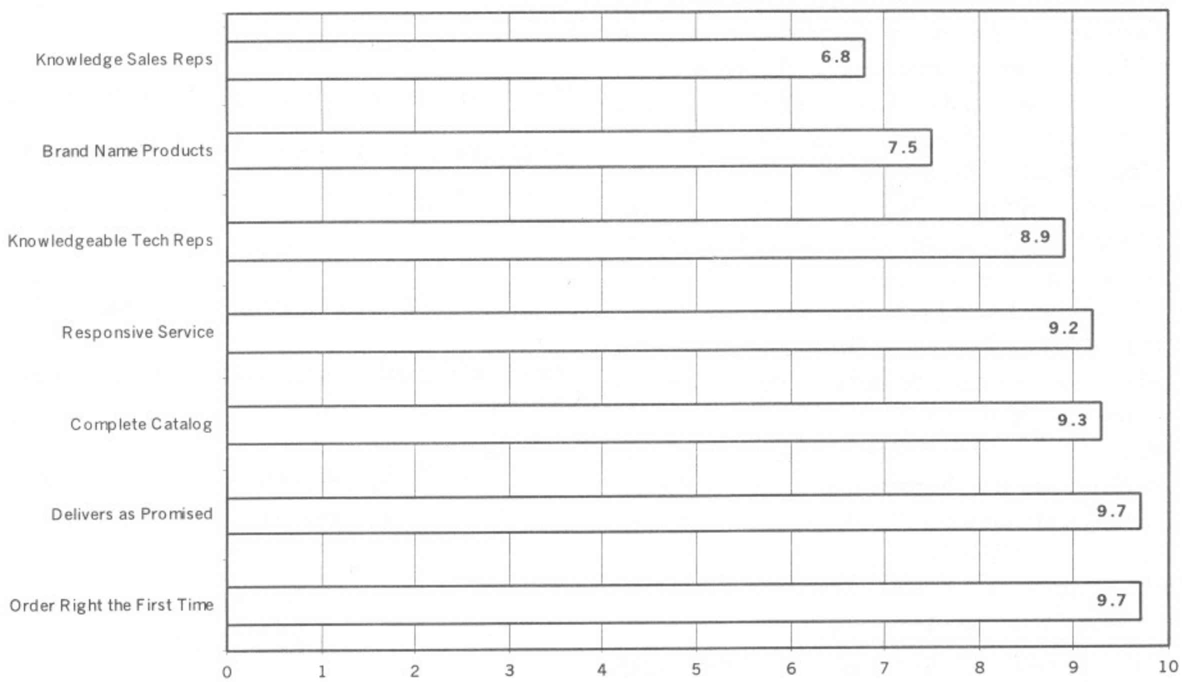
In other segmentation situations, a large number of choice alternatives (many suppliers or brand variations), handling non-measured strong local/regional brands/suppliers, or having a large number of explanatory variables, will require careful consideration by the researcher and may require alternative choice models that fit the situation. Baltas and Doyle (2001) provide a review of and references to methodologies that address each of these issues.

The approach described in this article incorporates consumer and competitor information that can be used to guide marketing decision–making. As marketing intelligence continues to become more prevalent, managerially useful data analysis techniques will grow in importance. Market oriented companies will benefit from segmentation schemes that are data driven but still remain intuitive as are the Loyal, Lost and Switchable segments.

TABLE 2
Influences on Choice of Supplier Coefficients

Variable	Coefficient	P-Value
Provides a complete catalog	-.717	.001
Delivers the order when promised	.553	.043
Carries brand name products	-.314	.147
Gets your order right the first time	-.515	.010
Has knowledgeable technical people you can call	-.015	.932
Have competent sales representatives that call on you	.118	.531
Provides responsive customer service	-4.01	.181

FIGURE 3
Direct Importance Ratings of Supplier Choice Drivers



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APPENDIX 1

Estimating the statistical significance of the difference in the deterministic component (A_{ij}) in equation 1 is equivalent to estimating the significance of difference in the choice probabilities (P_{ij}). The estimated value of A_{1i} is given by $\hat{A}_{1i}$:

$$\hat{A}_{1i} = \mathbf{B}^{1i}\hat{\mathbf{W}} \quad \text{where}$$

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

$\hat{\mathbf{W}}$ = a n x 1 vector of coefficients estimated by the logit model.

The variance associated with the difference between two deterministic components $(\hat{A}_{1i} - \hat{A}_{2i})$ would be:

$$V(\hat{A}_{1i} - \hat{A}_{2i}) = (b^{1i} - b^{2i})[\sigma^2(\hat{\mathbf{A}})](\mathbf{B}^{1i} - \mathbf{B}^{2i})$$

where

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

The test of the null hypothesis (no difference) at the 95% confidence level would be:

H_0: $A_{1i} \leq A_{2i}$ Do not reject H_0 if $z \leq 1.65$,
H_1: $A_{1i} > A_{2i}$ Reject H_0 if $z > 1.65$, where

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