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ON THE MULTIPLE SEGMENTATION PROBLEM: AN EMPIRICAL INVESTIGATION OF THE EFFICACY OF THE MULTIPLE LOGIT APPROACH IN PREDICTING SEGMENT MEMBERSHIP

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by

M. Lewis Temares

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Abstract

ON THE MULTIPLE SEGMENTATION PROBLEM: AN EMPIRICAL INVESTIGATION OF THE EFFICACY OF THE MULTIPLE LOGIT APPROACH IN PREDICTING SEGMENT MEMBERSHIP

by

M. Lewis Temares

Adviser: Professor Matthew Goldstein

The field of market segmentation as an area for investigation has been under scrutiny for many decades. The relevance of this area was denoted by a special issue of the Journal of Market Research in August of 1978 devoted to ten articles relating to market segmentation. In addition, the use of varied statistical techniques as predictive indicators with regard to buyer behavior has centered on the area of segmenting markets. Professor Paul Green has been the leader in this area and with his able co-authors has introduced the use of the logit loglinear model as a tool for analyzing consumer behavior in the market place and has dealt with the logit approach for a two group problem. Also, when dealing with the problem of market segmentation, only Roger Calantone and Alan Sawyer have dealt with segments remaining constant over a period

of time. This dissertation combines both of these areas of interest. Market Segmentation is investigated over two periods of time using panel data and analyzed utilizing the logit approach in order to develop a predictive model based upon demographic characteristics. The data are from two separate years for the same consumer panel. Validation of our approach is accomplished through the usual split-sample analysis. Thus, the two group approach of Professor Green is expanded to the multiple group problem and in combination with the panel data over time represents a situation not represented in the current literature.

Chapter One presents the reason for this study, the description of the data set and some background with regard to the market segmentation problem.

Chapter Two develops the background, rationale and mathematics for the use of the loglinear-logit approach to the market segmentation problem. It is a logical choice because discriminate analysis has become one of the most frequently used techniques for classification of data and the loglinear-logit analysis holds the greatest promise for effectively utilizing model building techniques.

Chapter Three involves the data presentation and computer analysis. The panel data is tested and a model utilizing the appropriate interactions of the variables is constructed.

Chapter Four includes the analysis of the data as presented in chapter three. The loglinear-logit analysis technique is utilized in order to predict the classification of the data through the construction of the appropriate discriminant function. A conclusion is reached on the basis of the data with regard to the efficacy of the multiple logit approach in predicting segment membership over time.

The final chapter, Chapter Five, includes a summary of the findings and presents avenues for possible future research. It is hoped that by using this dissertation as a foundation, further growth in the use of mathematical analysis for marketing decisions will be forthcoming. The sparseness of the data leads to the future possibility of an expansion of the current data base or applying the techniques to a different data base. This paper is not designed to test the data base used but uses this data base only to show how these statistical techniques are applied.

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To Nathan and Gertrude Temares who did not know when but still stuck in there,

To Professor Herbert Arkin without whom a multitude of quantitative analysts would never have come to be,

To Professor Matthew Goldstein a tireless teacher, adviser and critic,

To my friends and family who contended with my moods and offered support when I needed it,

I dedicate this dissertation with heartfelt thanks.

M. Lewis Temares

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CHAPTER 1

I. INTRODUCTION

The field of market segmentation as an area for investigation has been under scrutiny for many decades. The relevance of this area was denoted by a special issue of the Journal of Market Research in August of 1978 devoted to ten articles relating to market segmentation. In addition, the use of varied statistical techniques as predictive indicators with regard to buyer behavior has centered on the area of segmenting markets. Paul Green has been the leader in this area and with his able co-authors has introduced the use of the logit loglinear model as a tool for analyzing consumer behavior in the market place and has dealt with the logit approach for a two group problem. (25-37). Also, when dealing with the problem of market segmentation, only Roger Calantone and Alan Sawyer (13) have dealt with segments remaining constant over a period of time. The intent of this dissertation is to combine both of these areas of interest. Market Segmentation will be investigated over two periods of time using panel data and analyzed utilizing the logit approach in order to develop a predictive model based upon demographic characteristics. The data will be from two separate years for the same consumer panel. Validation of our approach will be accomplished through a usual split-sample analysis. In summary, the two group approach of Professor Green will be expanded to the multiple group problem and in combination with the panel data over time will represent a dissertation regarding a situation not previously dealt with in the literature.

II. STATEMENT OF THE PROBLEM

The problems confronting the researcher investigating the segmenting of markets are many. Basically the problem is to divide the market for a given product or type of product into strata that have meaning so that profit maximization can be achieved. More recently because of (1) the increased number of articles on the subject, (2) greater sophistication by the manager selecting the market segmentation strategies and (3) computer resource advances with regard to both software and hardware, emphasis has switched to the predictive powers of various statistical approaches. The problem that this paper will investigate is the efficacy of the multiple logit approach in predicting segment memberships over time.

This problem is worthy of research since a predictive model with regard to any market segment has been sought for decades. The key to this paper's uniqueness is that it will investigate the problem over time and will apply the multiple logit approach. Green, Carmone and Wachspress (29) have written on the two-group approach. However, this research represents an extension to the kth group and furthermore, the problem of predicting segment membership has never been attacked in the context of the logit log-linear model in the discrete case. The use of the logit model will provide "...an explicit parameterization of the problem, appropriate significance tests, and estimated probabilities for the criterion variable." (27,p.132)

The second aspect is equally significant; predictability over time. "However, the extent to which segments are stable over time is an important and neglected aspect of segmentation." (13,p.395) The goal in identifying market segments is to be able to reach a group in the market place with an appropriate approach to result in the purchase of particular goods and services. If conditions change over time, there is a likelihood that the market strategy will have to be altered as well. However, if it can be shown that the segments contain the same demographics for the consumers then strategies geared to reach these segments will not have to change. In other words, if segments remain constant over time with regard to their preferences, then the marketing plan geared towards the members of this segment need not be altered. The prediction of segment membership over time based upon demographic data is the objective of this study.

III. SURVEY OF THE LITERATURE

A. Market Segmentation

As noted previously, market segmentation has been under investigation for decades by market researchers. It began with Wroe Alderson viewing the idea of market segmentation from the aspect of analyzing existing data. Presently, the purpose is "...to provide a basis for identifying the data needed for strategy selection and implementation." (52)

A review and evaluation of the field of market segmentation research was accomplished by Frank, Massy, and Wind in 1972 (21) and updated by Wind in the Journal of Marketing Research in August, 1978. (59) An extensive listing of publications is included in the references.

B. Market Segmentation Over Time

An explicit examination of segment stability over time has not been accomplished other than by Calantone and Sawyer. "Most of the research in which time has been used in some way to define market segments has been based upon the expectation of changes over time." (13, p. 396) The approach used was through brand loyalty testing utilizing panel data.

Two other studies have viewed market segmentation in a dynamic environment. Myers and Nicosia (42,43) and Monroe and Guiltinah (40) did studies involving expected changes in market segmentation. However, these studies were based upon expectations while this research paper intends to utilize a priori segmentation and view the stability of the segments over time.

C. Loglinear Logit Approach

This statistical technique of fitting loglinear models to discrete multivariate data has been brought to the limelight by Paul Green and his co-authors in recent issues of the Journal of Marketing Research. (27,30) The technique of using loglinear models in relation to marketing issues using discrete statistical classifications has received limited attention in the literature. Most of the research has been centered upon the physical and social sciences until quite recently. Biship in Biometrics (5), Goodman in the American Journal of Sociology (24), and Theil in the American Journal of Sociology (56) represent the leaders in this area of statistical analysis. While Green has incorporated their ideas into a marketing framework, he has limited himself to an investigation of only the two group segmentation problem.

In conclusion, it is apparent that while the area of market segmentation has been widely examined, no one has investigated the efficacy of the multiple logit approach in predicting segment membership over time.

IV. DATA COLLECTION

The data set to be used is the same as the one mentioned in the Calantone and Sawyer (13) article. A sample of consumer panel people was drawn in a large metropolitan city in the great lakes region. The product class to be investigated was the retail banking market consisting of six banks - three savings and three commercial. The time periods for the 344 households questioned were 1972 and 1974. The predictor variables are all demographic and are listed with their codes in Chart 1. It is felt based upon recent studies that consumer behavior will be highly related to general characteristics of the households. Blattberg, Peacock and Sen corroborate this sentiment in their December, 1976 Journal of Consumer Research article, "Purchasing Strategies Across Product Categories." They say, "The principal implication of the ... results is that buying behavior may be more closely related to general characteristics of the household such as, demographics than might have been expected from past research in this area...it should be possible to find certain general customer characteristics which distinguish members of one segment from another." (8, p.154). Massy, Frank and Lodahl in Purchasing Behavior and Personal Attributes (41, p.6) also make a strong case for the use of demographic characteristics in segmentation research. "In spite of the relatively strong positions that have been taken in favor of segmentation based on psychological characteristics of customers: (1) there has been relatively little research published that provides an empirical basis for these conjectures; and (2) that which has been published supports the notion that where effects of psychological characteristics do exist they are relatively small."

Kaponen (40), Evans (16), Westfall (58) and the Advertising Research Foundation (1) report similar findings. Both Evans and Westfall refer to attempts to use knowledge of socio-economic and personality characteristics as predictors of customer automobile ownership. They found only a moderate association between personality and customer buying behavior. Kaponen and the ARF both examined the relationship between personality characteristics and customer buying behavior for various frequently purchased food

CHART 1

Predictor Variables and Codes

I. Total Money (TOTMONY) (M)
1. Small depositor
2. Large depositor

II. House (HOUSE) (H)
1. Apartment
2. Single Family House
3. Two Family House
4. Duplex
5. Other

III. Own (OWN) (O)
1. Own
2. Rent
3. Other

*IV. Education Level of Wife (WEDVC)
1. No education
2. Some Grammar School
3. Grammer School
4. Some H.S.
5. H.S. graduate
6. Some college
7. College graduate
8. Some Grad. School
9. Graduate degree

*V. Race
1-5 Minority or Immigrant
6 Majority

VI. Household Size (HHLSZ) (S)
1. 1 member
2. 2 member
3. 3 member
4. 4 member
5. 5 member
6. 6 member
7. 7 member
8. 8 or more members

*VII. Husband's Age (HUSAGE)
1. less than 25
2. 25-34
3. 35-44
4. 45-54
5. more than 55

*VIII. Cars
1. 1 car
2. 2 cars
3. 3 cars
4. 4 cars
5. 5 cars
6. 6 cars
7. 7 cars
8. 8 cars
9. 9 cars

IX. Household Income (HHINC) (I)
1. less than 12K
2. 12k-29,999
3. 30k and over

*Note:
Only a portion of the available demographic variables were used because of the sparseness conditions in the data. Those with asterisk were not included.

products. Kaponen found in his two studies that only 13% and 6% of the variance could be attributed to the variance in household socio-economic and personality characteristics.

The ARF study involved two-ply toilet tissue and the results virtually mirrored Kaponen's. Thus, while there may be a desire for a contrast of the relative efficacy of socio-economic and psychological characteristics (of which personality variables are one major class) and it may be important in light of the growing dissatisfaction with socio-economic characteristics as a basis for predicting the membership of customers in particular market segment groups, the author, based upon the data cited, has not seen the need for extending market analyses to include various psychological characteristics as a basis for identifying customer buying behavior segments. Future research in this area may prove fruitful but are behond the scope of this dissertation.

V. SUMMARY

Chapter One has been designed to present the reason and importance of this study. The description of the data set and some background with regard to the market segmentation problem have been presented. A justification has been stated for the scope of this dissertation.

Chapter Two will develop the background, rationale and mathematics for the use of the loglinear-logit approach to the market segmentation problem. It is a logical choice because discriminant analysis has become one of the most frequently used techniques for classification of data and the loglinear-logit analysis holds the greatest promise for effectively utilizing model building techniques.

Chapter Three will involve the data presentation and computer analysis. The panel data will be tested and a model utilizing the appropriate interactions of the variables will be constructed. Models will be fit for both the 1972 and 1974 data and when the final determination is made this model will be tested using the split sample technique.

Chapter Four includes the analysis of the data as presented in chapter three. The loglinear-logit analysis technique will be utilized in order to predict the classification of the data through the construction of the appropriate discriminant function. A conclusion will be reached on the basis of the data with regard to the efficacy of the multiple logit approach in predicting segment membership over time.

The final chapter, Chapter Five, will summarize the findings and present avenues for possible future research. It is hoped that by using this dissertation as a foundation, further growth in the use of mathematical analysis for marketing decisions will be forthcoming.

CHAPTER 2

LOGLINEAR - LOGIT APPROACH TO A PRIORI SEGMENTATION

Discriminant Analysis is one of the most frequently utilized techniques in the analysis of the a priori market segmentation problem. The well known linear discriminant function (LDF) or one of its many variants, is without question, the tool which most researchers utilize to effect classifications of observations whose population membership is unknown but known to belong to one and only one of k>1 groups. This technique is not without its limitations and indeed, much research activity has in the last few years been initiated through attempts at exploiting the underlying distributional properties of the populations involved to derive "optimal" rules.

A recent book by Goldstein and Dillon (23) deals exclusively with discriminant functions derived from an assumed multinomial structure to the data. In particular, such procedures are most appropriate when dealing with observations which are generated from questionnaires since demographic, attitudinal and preferential variables are most commonly measured on a discrete scale. Of the approaches discussed in the text, the authors indicate that loglinear-logit analysis holds the greatest promise for effectively utilizing model building techniques in constructing discriminant functions. The next few sections discuss this approach first in the a priori two cluster segmentation problem, and then to the extension of the K(>2) problem.

A LOGLINEAR - LOGIT APPROACH

The most comprehensive work to date on the subject of fitting loglinear models to discrete multivariate data is the text Discrete Multivariate Analysis by Biship, Fienberg and Holland (5).

In the field of marketing research this subject matter has gained in popularity as evidenced by two recent papers appearing in the Journal of Marketing Research (27,30). The problem of how to use loglinear models in relation to issues of discrete statistical classification, has, however, received insufficient attention in the literature. The purpose of this section is to suggest an approach to classification using these model representations for state probabilities.

For illustration and ease of notation we will discuss the case of a three-dimensional table. However, the results and ideas are completely general. Toward this end, suppose we represent the logarithm of the theoretical frequency m_{ijk} in cell (i,j,k) of a 2xJxK contingency table generated by variables X_1, X_2, X_3 as,

(1) $\ell n\ m_{ijk} = U{=}U_{1(i)} + U_{2(j)} + U_{3(k)} + U_{12(ij)} + U_{13(ik)} +$

$U_{23(jk)} + U_{123(ij)}$ where,

$\Sigma_i\ U_{1(i)} = \Sigma_j\ U_{2(j)} = \Sigma_k\ U_{3(k)} = 0$

$\Sigma_i\ U_{12(ij)} = \Sigma_i\ U_{13(ik)} = \Sigma_j\ U_{33(jk)} = 0;$

$$\Sigma_i U_{12(ij)} = \Sigma_k U_{13(ik)} = \Sigma_k U_{23(jk)} = 0$$
$$\Sigma_{ijk} U_{123(ijk)} = 0$$

The terms on the right-hand side of (1) are usually referred to as U-terms (parameters) and are interpretable, as in ANOVA models, in terms of individual and joint variable effects. Note also that for the problem considered here the variable X_1 is introduced to denote group membership - that is, $X_1 = 1$ (<=>)G. The other variables, X_2 and X_3, are considered due to their potential ability in discriminating between G_1 and G_2.

In almost all practical discussions the class of loglinear models is restricted to those models which satisfy the <u>hierarchical</u> property: if $\{\Theta\}$ and $\{\Theta'\}$ are any two sets of indices having the property $\{\Theta\}$ $\{\Theta'\}$, then $U_{\{\Theta\}} = 0$ implies $U_{\{\Theta'\}} = 0$ and, further, if $U_{\{\Theta\}} \neq 0$ then all U-terms containing subscripts which are a subset of $\{\Theta\}$ are also not zero. For instance, if $U_{12(ij)}$ is included in a model then the hierarchical principle states that $U_{1(i)}$ and $U_{2(j)}$ must also be present, whereas, if on the other hand $U_{12(ij)} = 0$ then we must have $U_{123(ijk)} = 0$. We will assume throughout our discussion that the loglinear models discussed have this property.

Viewing the multidimensional contingency table in the context of the discrimination problem and parroting the optimal rule we obtain the following assignment rule. Assign an individual with $X_2 = j$ and $X_3 = k$ to G_1 (G_2) if

$$(2) \quad \ln \frac{m_{1jk}}{m_{2jk}} > (<) \; 0$$

where again we have assumed equal prior probabilities. In addition, as we indicated earlier, the use of (2) requires as a first step the generation of observations either through sampling from the mixed population or from independent samples. With regard to estimation we could use the model given in (1) to estimate the left-hand side of (2). However, if maximum likelihood estimation is used to estimate all the parameters in (1), then nothing is gained through modeling since the values obtained for all states are the observed frequency counts. In most situations, loglinear models are employed to achieve a degree of parsimony with a "good fitting" unsaturated model -- that, one that contains few parameter estimates.

Specification of an unsaturated model can be most effectively accomplished by stating the sufficient configurations for the problem. For example, in the three variable problem, the sufficient configurations C_{12}, C_{13} would define the model.

$$(3) \quad \ln m_{ijk} = U + U_{1(i)} + U_{2(j)} + U_{3(k)} + U_{12(ij)} + U_{13(ik)}$$

Once the set of sufficient configurations is specified, maximum likelihood estimates are readily found either directly (i.e., estimates expressible in closed form) or through some iterative proportional fitting algorithm. Most computer algorithms use iterative proportional fitting whether or not direct estimates exist, and rely on a result which forces maximum likelihood estimates of marginal totals corresponding to specified sufficient configurations to be equal to observed marginal sums. Hence, if C_{12} and C_{13} are the sufficient configurations then the maximum likelihood estimates of the expected frequence totals $\hat{m}_{ij+}$ and $\hat{m}_{i+k}$ must satisfy the following:

$$(4)\quad \begin{aligned} \hat{m}_{ij+} &= f_{ij+} \\ \hat{m}_{i+k} &= f_{i+k} \end{aligned} \quad .$$

where f_{ij+} and f_{i+k} are the observed marginal sums. The degree to which the quality of the fitted model is any good can be determined by computing -2 times the logarithm of the likelihood-ratio test statistic used for testing that the model fitted is correct versus the unrestricted alternative. Under the hypothesis that the model is correct

$$(5)\quad G^2 = 2\Sigma_{ijk}\, f_{ijk}\, \ell n \left(\frac{f_{ijk}}{\hat{m}_{ijk}}\right)$$

is asymptotically X^2 with degrees of freedom equal to, # of states - # of independently fitted parameters. Note that in general the degrees of freedom will have to be adjusted if the fitted values contain zero estimates.

An asymptotically equivalent way to assess fit utilizes the familiar Pearson goodness-of-fit statistic

$$X^2 = \Sigma_{ijk} \ (f_{ijk} - \hat{m}_{ijk})^2 \ / \ \hat{m}_{ijk}.$$

However, we prefer using the likelihood ratio since G^2 is additive under partitioning for nested models; two models, M_1 and M_2, are said to be nested if all of the U-terms in M_1 are a subset of the U's contained in M_2. The difference in G^2 between the two models is a test of the additional effects in M_2 conditioned on the effects in M_1. This difference is asymptotically distributed as chi-square with degrees of freedom equal to the difference in the number of parameters fitted to the two models. This important property is not shared by the Pearson statistic.

Determining which hierarchical model to use generally can be determined through a series of U-term screenings. Goldstein (23) suggests using tests of partial and marginal associates for screening. The hypothesis that the partial association of k factors is zero is a test of whether a significant difference exists between the fit of two hierarchical models -- one is the full model of order k, and the other the model that differs from it in that the specified k-factor interaction is excluded. The hypothesis that the marginal association of k-factors is zero is a test that the k factor interaction is zero in the marginal subtable formed by the k factors. Both tests can be employed simultaneously to screen the various interactions to determine whether they are necessary in the model for the data being used, whether they are not necessary or whether they are questionable.

Goodman (24) suggests stepwise procedures for model selection. As an illustration we briefly discuss the case of a four-dimensional table. The procedure starts by selecting a specified $\alpha = \alpha_o$ level and an evaluation of the goodness-of-fit of the three models.

(1) $U_{12} = U_{13} = U_{14} = U_{23} = U_{24} = U_{34} = 0$

(2) $U_{123} = U_{124} = U_{134} = U_{234} = 0$

(3) $U_{1234} = 0$

If model (3) does not fit the data then we stop and choose the fully saturated design. If model (3) fits but not model (2) we start by considering the model C_{12}, C_{13}, C_{14}, C_{23}, C_{24}, C_{34} and successively add 3-factor terms according to the following rules:

(1) Add the 3-factor U-term to the model which will yield the most highly significant G^2.

(2) Using the induced model add the next mostly highly significant 3-factor U-term.

(3) Terminate the building process as soon as a 3-factor term yields a difference in G^2 which is nonsignificant.

The procedure can be done in a backwards mode or in a stepwise mode. In general, all three sequential procedures will result in different final models; however, they probably will be very similar.

LOGIT ANALYSIS

A special case of the loglinear model, which is especially relevant to the approach to be presented here, is the logit model. In logit analysis one or more variables are singled out as response measures, while the remaining variables are treated as explanatory variables. Interest focuses on the effects of the explanatory variables on the response variable(s). Continuing with the three variable problem, assume that X_1 is the variable of primary interest; in our case X_1 denotes group membership. Consider the loglinear model corresponding to no three-factor effect, i.e., $U_{123(ijk)} = 0$. With logit analysis we view the contingency table as an array of observed rates such that

(6) $f_{jk} = f_{1jk} / (f_{1jk} + f_{2jk})$

with corresponding logits given by

(7) $\text{logit } f_{jk} = \log (f_{1jk} / f_{2jk}) = \log f_{1jk} - \log f_{2jk}$

If we fit the no three-factor effect model then the logits of the estimated rates can easily be determined by substituting $\hat{m}_{1jk}$ and $\hat{m}_{2jk}$ for the observed counts in expression (7). Note, however, that the logits of the estimated rates depend only on 3 of the 7 parameters estimated in the no three-factor effect model. That is, we can express the model for the estimated logits as

$$(8)\ \text{logit}\ \hat{m}_{jk} = \log \hat{m}_{1jk} - \hat{m}_{2jk}$$
$$= (\hat{U}_{1(1)} - \hat{U}_{1(2)}) + (\hat{U}_{12\ (1j)} - \hat{U}_{12(2j)}) + (\hat{U}_{13(1k)} - \hat{U}_{13(2k)})$$
$$= \hat{W}_1 + \hat{W}_{3(k)}$$

where the W-terms have the same additive properties as their U-term counterparts.

In expression (8) the two-factor effect between variables X_2 and X_3 does not appear since it does not involve the response variable X_1 -- that is, the remaining parameters U_2, U_3, and U_{23} are the same for both f_{1jk} and f_{2jk}. This does not imply, however, that the logit equation is independent of the U-terms not including variable X_1. For instance, if we had specified $U_{23(jk)} = 0$, different estimates for $\hat{m}_{jk}$ would be obtained. There is a sublety here in the sense that specification of variable X_1 as the response measure and variables X_2 and X_3 as the explanatory factors means that the four sampling strata are, in a strict sense, determined by these two variables. In other words, "permissible" loglinear models must retain $U_{23(jk)}$ (and its lower-order relatives) so that the estimated margin totals equal observed totals since configuration C_{23} is fixed by the sampling plan. Though it is customary to include the highest-order configuration relating to the explanatory variables, it may be advantageous to exclude certain of the U-terms not involving variable X_1 if there is no rationale for treating the margin totals as fixed.

A RECURSIVE SYSTEM OF LOGITS

The data used in this research were collected over two time periods. Typically in such situations we are led to fit a recursive system of logit models; frequently one interprets the results under the umbrella of causality analysis.

To illustrate the methodology we propose to utilize, suppose we have four variables, A,B,C and D and we wish to assess the fit of a system of logit models associated with the causal ordering:

A precedes B precedes C precedes D. For example, A and C could represent demographic conditions for a class of respondents at time periods T_1 and T_2, $T_1 < T_2$ while B and D might represent the banks chosen by individuals to conduct their business. Consider the three logit models

1) A = explanatory, B = response
2) A,B = explanatory, C = response
3) A,B,C = explanatory, D = response

When these three models are combined, they characterize the conditional joint probability of B,C and D given A. The degree of goodness-of-fit for the recursive system of models can be determined by analyzing the fits of the component models. In general, the estimated expected cell values for the system will be expressed multiplicatively in terms of the expected values for the component models. The likelihood ratio statistic therefore, can be expressed as the sum of the G^2 statistics for the three component models.

Given that the overall recursive model yields an acceptable fit, we would then be in a position to fit logit models to the corresponding component loglinear models. The result of this analysis would be a recursive system of logit models. Path diagrams showing causal connections implied by the logit models can, if deemed appropriate be constructed; such diagrams are useful in interpreting interconnections between the variables.

LOGIT APPROACH FOR MULTIPLE SEGMENTS

Equation (2) displays an optimal assignment rule for the a priori two segment problem. Extension to the k segment problem under a similar theoretical framework provides the following allocation rule: Assignment to segment i if and only if

(9) $q_i m_{ijk} = \max \{q_t \, m_{tjk}\}$ where $q_1, \ldots\ldots, q_k$ are the prior segmentation membership probabilities. As before, loglinear representation for frequency counts are utilized to effectuate a useable sample-based allocation rule.

Logit Analysis is not as straightforward in the multiple problem as it is in the two group problem. In general, if there are k groups only, k-1 logit models are needed due to an inherent algebraic constraint. However, even so, it is not clear how one may wish to proceed. One possibility is to form the k-1 continuation ratios,

$$(10) \quad \ln \frac{m_{ijk}}{\sum_{s>i} m_{sjk}} \qquad ; i = 1,2,\ldots, K-1$$

In essence, this provides a log odds ratio for group i relative to the remaining groups.

Another approach would involve forming all possible pairwise logits,

$$(11) \quad \ln\left(\frac{m_{ijk}}{\Sigma_i m_{i+1,jk}}\right) \qquad ; i = 1,2,\ldots\ldots,K-1$$

as the basis of an allocation rule. In the latter case we would be looking at the odds ratios of being a depositor in one specified bank over another specified bank.

A primary objective in the analysis is to model bank preference (a response variable assuming more than two levels) to a set of demographic explanatory variables and a time variable. While it is not clear a priori to examining the data which set of logit models will best serve the data, we have the ability to express various log odds ratios into additive components so that patterns pertaining to bank preference will be identifiable.

CHAPTER 3

DATA PRESENTATION AND ANALYSIS

As previously noted, the major purpose of this thesis is to introduce and discuss through a marketing relevant data base a new class of statistical methodology useful in uncovering market segments. Thus, while the particular data set chosen is not of vital importance, the data base will assist us not so much in testing hypothesis but in illustrating a potent statistical tool. The data are described in Professors Roger Calantone and Alan Sawyer's article, "The Stability of Benefit Segments" in the August of 1978 edition of the Journal of Marketing Research (13). The data covers the years 1972 and 1974 and deal with individual bank depositors in either commercial or savings banks. Subjects from 1972 were traced in 1974 to determine whether they remained with the same bank, switched banks or switched types of banks. Thus, we have a data set involving subjects who were savings bank depositors or commercial bank depositors in 1972 and we are examining whether they stayed with a particular savings or commercial bank, stayed within the sub-group of savings or commercial bank, or switched from a savings to a commercial bank or vice-versa. Our analysis will be based upon 343 respondents. For modeling purposes all 343 subjects will be used, however, the usual split sample method (in our case 70% versus 30%) will be employed for validation.

RESEARCH DESIGN

Our primary purpose in this thesis is to demonstrate how a class of loglinear/logit models can be used to deal with the a priori market segmentation problem. In particular, our interest focuses on multiple segments and incorporating a time variable-both issues have received little attention in the literature. The sampling methodology resulted in a sample of 343 bank depositors from a consumer mail panel, in a large metropolitan midwestern city. Characteristics relating to the retail banking market for all respondents were recorded. This particular market was dominated by six banks; three commercial and three savings and the particular households were questioned at two time periods, two years apart; 1972, 1974. The demographics of the particular individuals were examined and it was determined to use six variables. The six variables chosen (with the original number and level types) were:

(1) Total money (M). This represents whether the person is a small depositor or a large depositor.

(2) The dwelling or house (H). Whether it was an apartment, single family house, two family house, duplex or other.

(3) Ownership (O). Whether the person owned, rented or was other with regard to the ownership of the dwelling.

(4) Household size (S). Ranging from one to eight or more members.

(5) Household income (I). Ranging from less than $4,000 all the way up to the category of $50,000 and over. Lastly, (6) the bank (B). Whether it was a commercial or savings bank.

While there were other variables available, we decided to reduce our variables to these five independent variables and one dependent variable. In the actual analysis, however, levels for some of the variables were collapsed because of severe sparseness. Appendix A lists the variables and the particular coding scheme for each of them, while Appendix B shows by computer output the initial marginal tables for the 1972 data. The model using the six variables, (keeping in mind that we are dealing with the bank depositors in either savings, commercial, both or neither) represents a 4x(3x3x2x2x2x) a cross-classification of 288 cells. This results in enormous sparseness and in general presents problems for which adequate solutions are in short supply.

Table I represents the saturated model for the 343 respondents from the 1972 sample. It will be noted that interactions up to the 6th order are examined. The purpose of this analysis is to examine the pertinent fit so that comparisons can be made between various models. Our intent is to arrive at a parsimonious model which will include the least number of interactions and still provide a good fit for the data. On pages 28-30 Table I we list the inter-

TABLE I

Marginal Total

Saturated Model

1972 Data

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	1	1	3	0
				LARGE	0	0	1	0
			OTHER	SMALL	1	4	1	1
				LARGE	1	0	3	0
		RENT	SINGLE	SMALL	0	2	3	2
				LARGE	0	0	1	0
			OTHER	SMALL	0	1	1	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	1	1	0	0
				LARGE	0	0	2	0
		RENT	SINGLE	SMALL	0	2	5	3
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	1	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	1	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	1	1
				LARGE	1	0	0	0
		RENT	SINGLE	SMALL	0	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	1	0
				LARGE	0	0	0	0

TABLE I (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	1	1	0	0
				LARGE	0	0	3	0
			OTHER	SMALL	1	7	7	0
				LARGE	1	1	4	0
		RENT	SINGLE	SMALL	1	4	1	1
				LARGE	0	1	2	0
			OTHER	SMALL	0	0	0	1
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	3	0
				LARGE	0	0	0	0
			OTHER	SMALL	5	18	19	5
				LARGE	0	0	9	0
		RENT	SINGLE	SMALL	1	11	12	3
				LARGE	0	0	1	0
			OTHER	SMALL	0	2	0	0
				LARGE	0	0	1	0
	5 or MORE	OWN	SINGLE	SMALL	0	2	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	3	13	17	2
				LARGE	0	1	7	0
		RENT	SINGLE	SMALL	0	1	5	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	3	2	0
				LARGE	0	0	0	0

TABLE I (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30k and over	1 or 2	OWN	SINGLE	SMALL	0	1	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	1	3	4	0
				LARGE	1	1	5	0
		RENT	SINGLE	SMALL	1	2	1	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	2	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	0	2	0
			OTHER	SMALL	1	7	8	2
				LARGE	1	0	10	0
		RENT	SINGLE	SMALL	1	0	3	0
				LARGE	0	1	1	0
			OTHER	SMALL	1	1	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	0	1	0
			OTHER	SMALL	3	6	11	3
				LARGE	1	1	8	0
		RENT	SINGLE	SMALL	1	0	1	1
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	1
				LARGE	0	0	0	0

TABLE Ia

Result of Fitting

All k-Factor Marginals

K-Factor	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB.
1	10	511.61	0.0000	1174.84	0.0000
2	40	292.22	0.0000	397.17	0.0000
3	82	65.10	.9147	71.11	.7991
4	91	82.96	.7140	108.00	.1079
5	52	1.18	1.0000	.64	1.0000
6	12	.33	1.0000	.17	1.0000

actions and, as can be noted at the third order interaction level we get a probability value for the likelihood ratio and for the Pearsonian chi-square that exceeds .05 and is relatively close to 1.0. Thus, we conclude that we need seek no further than at best the third order interaction with regard to the variables to be considered for our model.

Table II depicts the saturated model when we have added .5 to each cell which contains a zero frequency in order to obviate the sparseness problem. By examining Page 36, which depicts the table of the K factor interactions, we find that in this case, both fit statistics show clearly that a second order model is sufficient to describe the data. Although use of factor of 0.5 has created a more parsimonious model, it should be interpreted with caution.

The great advantages of the computerized age for fitting data and developing models was then brought in to use. All possible models were tested utilizing first order and second order interactions for a process of elimination of factors that did not contribute as significantly as other factors. A model was designed consisting of the interactions of household income and type of bank (IB), ownership of home and type of bank (HB), type of depositor being large or small and ownership (MO) household size and household income (SI), type of house and household size (HI), and all the first order interactions of

TABLE II**

SATURATED MODEL
WITH DELTA = 0.5

1972 DATA

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0-11,999	1 or 2	OWN	SINGLE	SMALL	1	1	3	0
				LARGE	0	0	1	0
			OTHER	SMALL	1	4	1	1
				LARGE	1	0	3	0
		RENT	SINGLE	SMALL	0	2	3	2
				LARGE	0	0	1	0
			OTHER	SMALL	0	1	1	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	1	1	0	0
				LARGE	0	0	2	0
		RENT	SINGLE	SMALL	0	2	5	3
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	1	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	1	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	1	1
				LARGE	1	0	0	0
		RENT	SINGLE	SMALL	0	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	1	0
				LARGE	0	0	0	0

TABLE II (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK(B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	1	1	0	0
				LARGE	0	0	3	0
			OTHER	SMALL	1	7	7	0
				LARGE	1	1	4	0
		RENT	SINGLE	SMALL	1	4	1	1
				LARGE	0	1	2	0
			OTHER	SMALL	0	0	0	1
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	3	0
				LARGE	0	0	0	0
			OTHER	SMALL	5	18	19	5
				LARGE	0	0	9	0
		RENT	SINGLE	SMALL	1	11	12	3
				LARGE	0	0	1	0
			OTHER	SMALL	0	2	0	0
				LARGE	0	0	1	0
	5 or MORE	OWN	SINGLE	SMALL	0	2	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	3	13	17	2
				LARGE	0	1	7	0
		RENT	SINGLE	SMALL	0	1	5	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	3	2	0
				LARGE	0	0	0	0

TABLE II (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30k and over	1 or 2	OWN	SINGLE	SMALL	0	1	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	1	3	4	0
				LARGE	1	1	5	0
		RENT	SINGLE	SMALL	1	2	1	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	2	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	0	2	0
			OTHER	SMALL	1	7	8	2
				LARGE	1	0	10	0
		RENT	SINGLE	SMALL	1	0	3	0
				LARGE	0	1	1	0
			OTHER	SMALL	1	1	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	0	1	0
			OTHER	SMALL	3	6	11	3
				LARGE	1	1	8	0
		RENT	SINGLE	SMALL	1	0	1	1
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	1
				LARGE	0	0	0	0

**For Analysis, .500 is Added to Each Cell Above
The Total Frequency is 343

TABLE IIa

Results of Fitting

All K-Factor Marginals

This is a simultaneous test that all k+1 and higher factor interactions are zero

k-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB.
0 (MEAN)	287	653.37	0.0000	1233.90	0.0000
1	277	301.51	.1491	347.94	.0024
2	237	107.65	1.0000	107.45	1.0000
3	155	53.89	1.0000	55.18	1.0000
4	64	16.52	1.0000	17.16	1.0000
5	12	1.45	.9999	1.46	.9999

A simultaneous test that all k-Factor interactions are zero. The entries are differences in the above table.

k-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB.
1	10	351.86	0.0000	885.96	0.0000
2	40	193.86	.0000	240.49	0.0000
3	82	53.76	.9933	52.27	.9957
4	91	37.37	1.0000	38.02	1.0000
5	52	15.07	1.0000	15.70	1.0000
6	12	1.45	.9999	1.46	.9999

household income, ownership, size, type of house, type of depositor, bank. To avoid this kind of verbalization in future discussions, it is to be realized that when a higher order of interaction is considered for a model, the lower order interactions have to be included as well. (This is a technical issue discussed in the previous chapter relating to a restriction on the type of hierarchical models which we utilize throughout our discussion). In other words, if we are dealing with an interaction of household income and bank (IB) as second order, the first order of household income (I) and the first order banking (B) have to be included as well. Thus, we will eliminate the repetition once we deal with the higher orders in the future.

Table III shows the fitted values for the model depicted above. As you will note the standardized residual values do not vary greatly from zero and are seemingly symmetrical, and contain both positive and negative values. As noted, standardized residuals equals the observed value minus the fitted value all over the square root of the fitted value. (S.R.$=(O-F)/\sqrt{F}$) This is found in Table IIIa. The standardized residual values are utilized to depict aberrant behavior at the particular cell levels. A cursory examination will show the reader that there is no apparent aberrant behavior Tukey deviates are also included as a validation to the more familiar standardized residuals.

1974 DATA

The same techniques that were used for the 1972 data

TABLE III

FITTED VALUES

1972 DATA

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	.270	.590	1.194	.262
				LARGE	.101	.221	.447	.098
			OTHER	SMALL	1.212	2.650	5.359	1.178
				LARGE	.454	.992	2.006	.441
		RENT	SINGLE	SMALL	.523	2.102	3.187	1.500
				LARGE	.060	.242	.366	.172
			OTHER	SMALL	.088	.354	.537	.253
				LARGE	.010	.041	.062	.029
	3 or 4	OWN	SINGLE	SMALL	.138	.302	.611	.134
				LARGE	.052	.113	.229	.050
			OTHER	SMALL	.789	1.725	3.489	.767
				LARGE	.295	.646	1.306	.287
		RENT	SINGLE	SMALL	.268	1.076	1.631	.768
				LARGE	.031	.124	.188	.088
			OTHER	SMALL	.057	.230	.349	.164
				LARGE	.007	.026	.040	.019
	5 or MORE	OWN	SINGLE	SMALL	.025	.054	.109	.024
				LARGE	.009	.020	.041	.009
			OTHER	SMALL	.384	.839	1.697	.373
				LARGE	.144	.314	.635	.110
		RENT	SINGLE	SMALL	.048	.193	.292	.137
				LARGE	.006	.022	.034	.016
			OTHER	SMALL	.028	.112	.170	.080
				LARGE	.003	.013	.020	.009

TABLE III (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	.248	1.082	1.690	.179
				LARGE	.093	.405	.632	.067
			OTHER	SMALL	1.116	4.859	7.585	.806
				LARGE	.418	1.819	2.839	.302
		RENT	SINGLE	SMALL	.481	3.854	4.511	1.025
				LARGE	.055	.443	.519	.118
			OTHER	SMALL	.081	.649	.760	.173
				LARGE	.009	.075	.087	.020
	3 or 4	OWN	SINGLE	SMALL	.527	2.297	3.586	.381
				LARGE	.197	.860	1.342	.143
			OTHER	SMALL	3.012	13.118	20.478	2.175
				LARGE	1.127	4.910	7.665	.814
		RENT	SINGLE	SMALL	1.021	8.181	9.575	2.176
				LARGE	.117	.940	1.101	.250
			OTHER	SMALL	.219	1.753	2.051	.466
				LARGE	.025	.201	.236	.054
	5 or MORE	OWN	SINGLE	SMALL	.163	.709	1.107	.118
				LARGE	.061	.265	.414	.044
			OTHER	SMALL	2.527	11.005	12.179	1.824
				LARGE	.946	4.119	6.430	.683
		RENT	SINGLE	SMALL	.315	2.525	2.955	.671
				LARGE	.036	.290	.340	.077
			OTHER	SMALL	.184	1.470	1.721	.391
				LARGE	.021	.169	.198	.045

TABLE III (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30k and over	1 or 2	OWN	SINGLE	SMALL	.271	.505	1.283	.131
				LARGE	.101	.189	.480	.049
			OTHER	SMALL	1.216	2.269	5.762	.590
				LARGE	.455	.849	2.157	.221
		RENT	SINGLE	SMALL	.525	1.800	3.427	.750
				LARGE	.060	.207	.394	.086
			OTHER	SMALL	.088	.303	.577	.126
				LARGE	.010	.035	.066	.015
	3 or 4	OWN	SINGLE	SMALL	.383	.714	1.814	.186
				LARGE	.143	.267	.679	.069
			OTHER	SMALL	2.186	4.079	10.359	1.060
				LARGE	.818	1.527	3.877	.397
		RENT	SINGLE	SMALL	.741	2.544	4.844	1.061
				LARGE	.085	.292	.557	.122
			OTHER	SMALL	.159	.545	1.038	.227
				LARGE	.018	.063	.119	.026
	5 or MORE	OWN	SINGLE	SMALL	.181	.338	.860	.088
				LARGE	.068	.127	.322	.033
			OTHER	SMALL	2.816	5.254	13.342	1.365
				LARGE	1.054	1.966	4.224	.511
		RENT	SINGLE	SMALL	.351	1.205	2.295	.503
				LARGE	.040	.139	.264	.058
			OTHER	SMALL	.205	.702	1.336	.293
				LARGE	.024	.081	.154	.034

TABLE III a

STANDARDIZED RESIDUALS

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	1.405	.533	1.653	-.512
				LARGE	-.318	-.470	.828	-.313
			OTHER	SMALL	-.193	.830	-1.883	-.164
				LARGE	.811	-.996	.702	-.664
		RENT	SINGLE	SMALL	-.723	-.070	-.105	.409
				LARGE	-.245	-.492	1.047	-.415
			OTHER	SMALL	-.297	1.086	.632	-.503
				LARGE	-.101	-.202	-.248	-.170
	3 or 4	OWN	SINGLE	SMALL	-.372	1.270	-.782	-.367
				LARGE	-.227	-.336	-.478	-.224
			OTHER	SMALL	.238	-.552	-1.868	-.876
				LARGE	-.543	-.804	.607	-.536
		RENT	SINGLE	SMALL	-.517	.891	2.637	2.548
				LARGE	-.175	-.352	-.433	-.297
			OTHER	SMALL	-.239	-.480	1.100	-.405
				LARGE	-.081	-.163	-.200	-.137
	5 or MORE	OWN	SINGLE	SMALL	-.157	-.233	2.693	-.155
				LARGE	-.096	-.142	-.202	-.095
			OTHER	SMALL	-.620	-.916	-.535	1.026
				LARGE	2.259	-.560	-.797	-.374
		RENT	SINGLE	SMALL	-.219	-.439	-.540	-.371
				LARGE	-.074	-.149	-.183	-.126
			OTHER	SMALL	-.167	2.652	2.013	-.283
				LARGE	-.157	-.114	-.140	-.096

TABLE III a (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	1.508	-.079	-1.300	-.424
				LARGE	-.305	-.636	2.977	-.259
			OTHER	SMALL	-.109	.971	-.212	-.898
				LARGE	.901	-.607	.689	-.549
		RENT	SINGLE	SMALL	.748	.074	-1,653	-.025
				LARGE	-.238	.837	2.057	-.343
			OTHER	SMALL	-.285	-.806	-.872	1.991
				LARGE	-.097	-.273	-.294	-.141
	3 or 4	OWN	SINGLE	SMALL	-.726	-.856	-.310	-.617
				LARGE	-.444	-.927	-1.159	-.378
			OTHER	SMALL	1.146	1.348	-.327	1.916
				LARGE	-1.062	-2.216	.482	-.902
		RENT	SINGLE	SMALL	-.021	.985	.784	.559
				LARGE	-.343	-.970	-.096	-.500
			OTHER	SMALL	-.468	.187	-1.432	-.683
				LARGE	-.159	-.449	1.574	-.231
	5 or MORE	OWN	SINGLE	SMALL	-.403	1.533	-1.052	2.574
				LARGE	-.247	-.515	.910	-.210
			OTHER	SMALL	.298	.601	-.043	.130
				LARGE	-.972	-1.537	.225	-.826
		RENT	SINGLE	SMALL	-.561	-.960	1.190	-.819
				LARGE	-.190	-.539	1.133	-.278
			OTHER	SMALL	-.428	1.262	.213	-.625
				LARGE	-.145	-.411	-.445	-.212

TABLE III a (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30K and Over	1 or 2	OWN	SINGLE	SMALL	-.520	.696	-1.133	2.397
				LARGE	-.318	-.435	.750	-.222
			OTHER	SMALL	-.196	.485	-.734	-.768
				LARGE	.808	.164	1.936	-.470
		RENT	SINGLE	SMALL	.656	.149	-1.311	-.866
				LARGE	-.246	-.455	.966	-.294
			OTHER	SMALL	-.297	-.551	1.873	-.355
				LARGE	-.101	-.187	-.258	-.121
	3 or 4	OWN	SINGLE	SMALL	-.619	.338	-.604	-.431
				LARGE	-.379	-.517	1.603	-.264
			OTHER	SMALL	-.802	1.446	-.733	.913
				LARGE	.201	-1.236	3.109	-.630
		RENT	SINGLE	SMALL	.300	-1.595	-.838	-1.030
				LARGE	-.292	1.309	.594	-.349
			OTHER	SMALL	2.111	.616	-1.019	-.477
				LARGE	-.135	-.250	-.345	-.162
	5 or MORE	OWN	SINGLE	SMALL	-.426	1.137	.152	-.297
				LARGE	-.261	-.356	1.196	-.181
			OTHER	SMALL	.110	.326	-.641	1.399
				LARGE	-.053	-.689	1.345	-.715
		RENT	SINGLE	SMALL	1.095	-1.098	-.855	.702
				LARGE	-.201	-.372	-.514	-.240
			OTHER	SMALL	-.452	.356	-1.156	1.308
				LARGE	-.153	-.284	-.392	-.183

TABLE III b

FREEMAN - TUKEY DEVIATES

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	.972	.581	1,329	-.432
				LARGE	-.185	-.372	.745	-.180
			OTHER	SMALL	-.004	.830	-2,323	.024
				LARGE	.737	-1.229	.728	-.663
		RENT	SINGLE	SMALL	-.758	.079	.024	.501
				LARGE	-.114	-.402	.844	-.300
			OTHER	SMALL	-.163	.860	.640	-.418
				LARGE	-.020	-.078	-.117	-.056
	3 or 4	OWN	SINGLE	SMALL	-.246	.928	-.856	-.240
				LARGE	-.099	-.205	-.384	-.096
			OTHER	SMALL	.376	-.396	-2,867	-1,017
				LARGE	-.477	-.893	.651	-.466
		RENT	SINGLE	SMALL	-.439	.843	1,942	1.715
				LARGE	-.060	-.223	-.323	-.163
			OTHER	SMALL	-.109	-.386	.866	-.287
				LARGE	-.013	-.052	-.077	-.037
	5 or MORE	OWN	SINGLE	SMALL	-.048	-.103	1.215	-.047
				LARGE	-.018	-.040	-.079	-.018
			OTHER	SMALL	-.592	-1.087	-.377	.835
				LARGE	1.159	-.502	-.882	-.249
		RENT	SINGLE	SMALL	-.092	-.330	-.472	-.245
				LARGE	-.011	-.043	-.065	-.031
			OTHER	SMALL	-.054	1.211	1.118	-.149
				LARGE	-.006	-.025	-.038	-.018

TABLE III b (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	1.002	.106	-1.785	-.311
				LARGE	-.171	-.619	1.853	-.126
			OTHER	SMALL	.077	.954	-.124	-1.055
				LARGE	.780	-.462	.721	-.485
		RENT	SINGLE	SMALL	.704	.184	-1.950	.156
				LARGE	-.105	.749	1.393	-.213
			OTHER	SMALL	-.151	-.896	-1.010	1.114
				LARGE	-.018	-.139	-.162	-.039
	3 or 4	OWN	SINGLE	SMALL	-.763	-.778	-.185	-.589
				LARGE	-.338	-1.107	-1.524	-.253
			OTHER	SMALL	1.073	1.289	-.275	1.571
				LARGE	-1.347	-3.543	.536	-1.063
		RENT	SINGLE	SMALL	.159	.973	.801	.617
				LARGE	-.212	-1.182	.090	-.414
			OTHER	SMALL	-.369	.316	-2.034	-.692
				LARGE	-.049	-.344	1.020	-.102
	5 or MORE	OWN	SINGLE	SMALL	-.285	1.188	-1.330	1.202
				LARGE	-.115	-.436	.784	-.084
			OTHER	SMALL	.399	.638	.016	.266
				LARGE	-1.187	-1.766	.305	-.932
		RENT	SINGLE	SMALL	-.504	-.917	1.105	-.920
				LARGE	-.070	-.470	.878	-.144
			OTHER	SMALL	-.317	1.109	.339	-.601
				LARGE	-.041	-.295	-.388	-.086

TABLE III b (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30K and over	1 or 2	OWN	SINGLE	SMALL	-.443	.676	-1.477	1.179
				LARGE	-.186	-.325	.705	-.094
			OTHER	SMALL	-.007	.558	-.668	-.833
				LARGE	.735	.317	1.583	-.372
		RENT	SINGLE	SMALL	.654	.283	-1.421	-1.000
				LARGE	-.114	-.352	.809	-.160
			OTHER	SMALL	-.163	-.487	1.327	-.227
				LARGE	-.020	-.067	-.125	-.029
	3 or 4	OWN	SINGLE	SMALL	-.591	.450	-.459	-.320
				LARGE	-.254	-.439	1.219	-.130
			OTHER	SMALL	-.707	1.313	-.686	.857
				LARGE	.347	-1.666	2.416	-.608
		RENT	SINGLE	SMALL	.423	-2.343	-.782	-1.290
				LARGE	-.158	.941	.618	-.220
			OTHER	SMALL	1.135	.631	-1.269	-.382
				LARGE	-.036	-.118	-.215	-.051
	5 or MORE	OWN	SINGLE	SMALL	-.314	.880	.308	-.163
				LARGE	-.128	-.227	.902	-.064
			OTHER	SMALL	.230	.403	-.593	1.190
				LARGE	.130	-.563	1.249	-.745
		RENT	SINGLE	SMALL	.863	-1.413	-.776	.679
				LARGE	-.078	-.247	-.434	-.110
			OTHER	SMALL	-.348	.463	-1.519	.941
				LARGE	-.046	-.150	-.271	-.065

were also applied to the 1974 data. Table IV shows a table for the 343 observations with 288 cells. Again, the table is examined and an appropriate unsaturated model can be determined. Table V represents the fully saturated table utilizing a delta .5 in all the cells which contain zero. Again it must be noted that since we have 288 cells and only 343 frequencies, obviously there is sparseness in the table. By adding this delta factor, the table of K factors depicting the appropriate likelihood ratio probability and Pearson chi-square probability determines that models containing third order interactions are required. Again, through many iterations it was determined that the appropriate higher order model would contain BHO, BSI, HS, OS, MO, MS, MI, HI. The fitted values for this model can be examined in the beginning of Table VI. On Page 59 of Table VI, the standardized residuals are calculated in a similar manner as was done for the 1972 data. Again, these Freeman-Tukey deviates are examined; the generated values appear to be symmetrical around zero with a similar number of pluses and minuses leading us to believe that we have both a parsimonious and good fit.

FITTING THE 1972 MODEL TO THE 1974 DATA

Examining both the 1972 data and the 1974 data has resulted in two different models being developed. To see if either of these models would be most appropriate

TABLE IV
MARGINAL TOTAL
SATURATED MODEL

1974 DATA

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	1	0	2	2
				LARGE	0	0	1	0
			OTHER	SMALL	1	1	0	4
				LARGE	1	1	5	0
		RENT	SINGLE	SMALL	0	2	3	5
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	0	1
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	0	0	3
				LARGE	0	0	0	0
			OTHER	SMALL	1	3	0	1
				LARGE	0	0	0	0
		RENT	SINGLE	SMALL	0	2	3	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	0	1
				LARGE	1	0	0	0
			OTHER	SMALL	1	0	1	1
				LARGE	0	0	0	0
		RENT	SINGLE	SMALL	0	1	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	0
				LARGE	0	0	0	0

TABLE IV (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12K - 29,999	1 or 2	OWN	SINGLE	SMALL	1	2	0	2
				LARGE	0	0	2	0
			OTHER	SMALL	3	6	2	3
				LARGE	2	2	12	0
		RENT	SINGLE	SMALL	2	0	2	1
				LARGE	0	1	1	0
			OTHER	SMALL	0	0	2	0
				LARGE	0	0	1	0
	3 or 4	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	1	2	0
			OTHER	SMALL	13	9	23	8
				LARGE	3	1	9	0
		RENT	SINGLE	SMALL	8	9	8	3
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	1
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	1	1	3	1
				LARGE	0	0	1	0
			OTHER	SMALL	9	11	12	7
				LARGE	2	0	8	0
		RENT	SINGLE	SMALL	1	1	5	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	3	2	0
				LARGE	0	0	0	0

TABLE IV (Continued

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30K and over	1 or 2	OWN	SINGLE	SMALL	1	0	0	0
				LARGE	1	0	0	0
			OTHER	SMALL	2	2	2	1
				LARGE	3	0	4	0
		RENT	SINGLE	SMALL	0	0	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	1	0	0	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	0	0	1
				LARGE	1	0	2	0
			OTHER	SMALL	4	4	4	1
				LARGE	1	0	4	0
		RENT	SINGLE	SMALL	1	1	1	0
				LARGE	1	0	0	0
			OTHER	SMALL	1	0	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	1	8	8	1
				LARGE	2	2	7	0
		RENT	SINGLE	SMALL	1	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	0	0
				LARGE	0	0	0	0

TABLE IV a

RESULT OF FITTING
ALL K-FACTOR MARGINALS

K-FACTOR	D.F	LR CHISQ	PROB	PEARSON CHISQ	PROB.
1	10	435.63	0.0000	838.17	0.0000
2	40	324.80	0.0000	561.93	0.0000
3	82	80.15	.5373	104.75	.0459
4	91	18.17	.5942	106.28	.1305
5	52	.79	1.0000	.40	1.0000
6	12	.16	1.0000	.08	1.0000

TABLE V
SATURATED MODEL
WITH DELTA = 0.5

1974 DATA

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	1	0	2	2
				LARGE	0	0	1	0
			OTHER	SMALL	1	1	0	4
				LARGE	1	1	5	0
		RENT	SINGLE	SMALL	0	2	3	5
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	0	1
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	0	0	3
				LARGE	0	0	0	0
			OTHER	SMALL	1	3	0	1
				LARGE	0	0	0	0
		RENT	SINGLE	SMALL	0	2	3	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	0	1
				LARGE	1	0	0	0
			OTHER	SMALL	1	0	1	1
				LARGE	0	0	0	0
		RENT	SINGLE	SMALL	0	1	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	0
				LARGE	0	0	0	0

TABLE V (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	1	2	0	2
				LARGE	0	0	2	0
			OTHER	SMALL	3	6	2	3
				LARGE	2	2	12	0
		RENT	SINGLE	SMALL	2	0	2	1
				LARGE	0	1	1	0
			OTHER	SMALL	0	0	2	0
				LARGE	0	0	1	0
	3 or 4	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	1	2	0
			OTHER	SMALL	13	9	23	8
				LARGE	3	1	9	0
		RENT	SINGLE	SMALL	6	9	8	3
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	1
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	1	1	3	1
				LARGE	0	0	1	0
			OTHER	SMALL	9	11	12	7
				LARGE	2	0	6	0
		RENT	SINGLE	SMALL	1	1	5	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	3	2	0
				LARGE	0	0	0	0

TABLE V (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30K and over	1 or 2	OWN	SINGLE	SMALL	1	0	0	0
				LARGE	1	0	0	0
			OTHER	SMALL	2	2	2	1
				LARGE	3	0	4	0
		RENT	SINGLE	SMALL	0	0	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	1	0	0	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	0	0	1
				LARGE	1	0	2	0
			OTHER	SMALL	4	4	4	1
				LARGE	1	0	4	0
		RENT	SINGLE	SMALL	1	1	1	0
				LARGE	1	0	0	0
			OTHER	SMALL	1	0	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	1	8	8	1
				LARGE	2	2	7	0
		RENT	SINGLE	SMALL	1	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	0	0
				LARGE	0	0	0	0

TABLE V a

1974 DATA

RESULTS OF FITTING
ALL K-FACTOR MARGINALS

K-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB
0 (MEAN)	287	626.57	0.0000	1132.13	0.0000
1	277	323.76	.0279	416.85	.0000
2	237	125.31	1.0000	129.13	1.0000
3	155	59.13	1.0000	60.40	1.0000
4	64	12.49	1.0000	13.14	1.0000
5	12	1.28	.9999	1.28	.9999

A Simultaneous Test That All K-Factor Interactions Are Zero.
The Entries Are Differences In The Above Table.

K-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB
1	10	302.81	0.0000	715.28	0.0000
2	40	198.44	.0000	287.72	0.0000
3	82	66.19	.8983	68.74	.8519
4	91	46.64	1.0000	47.26	1.0000
5	52	11.21	1.0000	11.86	1.0000
6	12	1.28	.9999	1.28	.9999

TABLE VI

FITTED VALUES OF THE MODEL

1974 DATA

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	.367	.304	1.385	2.218
				LARGE	.227	.189	.859	1.375
			OTHER	SMALL	.788	.985	3.174	2.732
				LARGE	.488	.611	1.968	1.693
		RENT	SINGLE	SMALL	.944	1.526	3.810	3.197
				LARGE	.127	.206	.514	.431
			OTHER	SMALL	.051	.157	.254	.308
				LARGE	.007	.021	.034	.042
	3 or 4	OWN	SINGLE	SMALL	.162	.497	.612	.986
				LARGE	.030	.091	.112	.180
			OTHER	SMALL	.324	1.492	1.303	1.127
				LARGE	.059	.272	.238	.206
		RENT	SINGLE	SMALL	.390	2.327	1.573	1.328
				LARGE	.015	.092	.062	.053
			OTHER	SMALL	.020	.222	.097	.119
				LARGE	.001	.009	.004	.005
	5 or MORE	OWN	SINGLE	SMALL	.273	.173	.129	.422
				LARGE	.044	.028	.021	.069
			OTHER	SMALL	1.017	.972	.511	.901
				LARGE	.165	.158	.083	.147
		RENT	SINGLE	SMALL	.443	.548	.223	.383
				LARGE	.016	.019	.008	.014
			OTHER	SMALL	.041	.098	.026	.064
				LARGE	.001	.003	.001	.002

TABLE VI (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	.470	.406	1.213	.560
				LARGE	.415	.359	1.071	.495
			OTHER	SMALL	2.893	3.766	7.956	1.974
				LARGE	2.556	3.326	7.028	1.744
		RENT	SINGLE	SMALL	1.211	2.038	3.335	.807
				LARGE	.233	.391	.641	.155
			OTHER	SMALL	.187	.601	.636	.223
				LARGE	.036	.115	.122	.043
	3 or 4	OWN	SINGLE	SMALL	1.936	1.195	3.545	1.673
				LARGE	.503	.311	.922	.435
			OTHER	SMALL	11.059	10.283	21.590	5.477
				LARGE	2.876	2.674	5.614	1.424
		RENT	SINGLE	SMALL	4.658	5.600	9.109	2.253
				LARGE	.263	.317	.515	.127
			OTHER	SMALL	.667	1.532	1.612	.577
				LARGE	.038	.087	.091	.033
	5 or MORE	OWN	SINGLE	SMALL	.786	.614	1.642	.787
				LARGE	.182	.143	.381	.182
			OTHER	SMALL	8.387	9.871	18.670	4.807
				LARGE	1.945	2.289	4.330	1.115
		RENT	SINGLE	SMALL	1.276	1.942	2.846	.715
				LARGE	.064	.098	.144	.136
			OTHER	SMALL	.341	.992	.940	.341
				LARGE	.017	.050	.047	.017

TABLE VI (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30k and over	1 or 2	OWN	SINGLE	SMALL	.227	.036	.186	.092
				LARGE	.428	.068	.351	.173
			OTHER	SMALL	2.191	.527	1.915	.509
				LARGE	4.134	.995	3.614	.959
		RENT	SINGLE	SMALL	.584	.182	.511	.132
				LARGE	.240	.075	.210	.054
			OTHER	SMALL	.141	.084	.153	.057
				LARGE	.058	.034	.063	.024
	3 or 4	OWN	SINGLE	SMALL	.478	.166	.547	.171
				LARGE	.266	.092	.304	.095
			OTHER	SMALL	4.292	2.246	5.231	.881
				LARGE	2.384	1.247	2.905	.489
		RENT	SINGLE	SMALL	1.151	.779	1.405	.231
				LARGE	.139	.094	.170	.028
			OTHER	SMALL	.259	.335	.391	.093
				LARGE	.031	.040	.047	.011
	5 or MORE	OWN	SINGLE	SMALL	.137	.220	.482	.057
				LARGE	.068	.109	.239	.028
			OTHER	SMALL	2.303	5.540	8.600	.545
				LARGE	1.141	2.744	4.264	.270
		RENT	SINGLE	SMALL	.223	.694	.835	.052
				LARGE	.024	.075	.090	.006
			OTHER	SMALL	.094	.557	.434	.039
				LARGE	.010	.060	.047	.004

TABLE VI a

STANDARDIZED RESIDUALS

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	1.046	-.552	.522	-.146
				LARGE	-.477	-.434	.152	-1.173
			OTHER	SMALL	.239	.015	-1.782	.767
				LARGE	.732	.498	2.162	-1.301
		RENT	SINGLE	SMALL	-.972	.383	-.415	1.008
				LARGE	-.357	-.454	.679	-.656
			OTHER	SMALL	-.226	-.396	-.504	1.247
				LARGE	-.083	-.146	-.185	-.204
	3 or 4	OWN	SINGLE	SMALL	-.403	-.705	-.783	2.029
				LARGE	-.172	-.301	-.334	-.424
			OTHER	SMALL	1.189	1.234	-1.141	-.120
				LARGE	-.243	-.522	-.488	-.454
		RENT	SINGLE	SMALL	-.625	-.214	1.137	-1.152
				LARGE	-.124	-.304	3.752	-.230
			OTHER	SMALL	-.140	-.472	-.312	-.345
				LARGE	-.028	-.094	-.062	-.069
	5 or MORE	OWN	SINGLE	SMALL	-.522	-.416	-.359	.890
				LARGE	4.534	-.168	-.145	-.262
			OTHER	SMALL	-.017	-.986	.685	.105
				LARGE	-.407	-.398	-.288	-.383
		RENT	SINGLE	SMALL	-.665	.611	-.472	-.619
				LARGE	-.125	-.139	-.089	-.116
			OTHER	SMALL	-.203	2.886	-.160	-.253
				LARGE	-.038	-.059	-.030	-.048

TABLE VI a (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	.773	2.500	-1.101	1.925
				LARGE	-.644	-.599	.897	-.703
			OTHER	SMALL	.063	1.151	-2.112	.730
				LARGE	-.348	-.727	1.875	-1.321
		RENT	SINGLE	SMALL	.717	-1.427	-.731	.215
				LARGE	-.482	.973	.449	-.394
			OTHER	SMALL	-.432	-.775	1.710	-.472
				LARGE	-.189	-.340	2.512	-.207
	3 or 4	OWN	SINGLE	SMALL	-1.391	-.178	-1.352	-1.294
				LARGE	-.709	1.236	1.123	-.660
			OTHER	SMALL	.584	-.400	.303	1.078
				LARGE	.073	-1.024	1.429	-1.193
		RENT	SINGLE	SMALL	.622	1.437	-.367	.497
				LARGE	-.513	-.563	-.718	-.357
			OTHER	SMALL	-.817	-.430	-1.270	.557
				LARGE	-.194	-.294	-.302	-.181
	5 or MORE	OWN	SINGLE	SMALL	.241	.492	1.060	.241
				LARGE	-.427	-.378	1.003	-.427
			OTHER	SMALL	.212	.359	-1.544	1.000
				LARGE	.039	-1.513	.802	-1.056
		RENT	SINGLE	SMALL	-.244	-.676	1.277	-.845
				LARGE	-.254	-.313	-.379	-.190
			OTHER	SMALL	-.584	2.016	1.093	-.584
				LARGE	-.131	-.224	-.218	-.131

TABLE VI a (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30k and over	1 or 2	OWN	SINGLE	SMALL	1.624	-.190	-.431	-.303
				LARGE	.875	-.261	-.592	-.416
			OTHER	SMALL	-.129	2.029	.061	.689
				LARGE	-.558	-.997	.203	-.980
		RENT	SINGLE	SMALL	-.764	-.426	-.715	2.385
				LARGE	-.489	-.273	1.726	-.233
			OTHER	SMALL	2.283	-.290	-.391	-.239
				LARGE	-.241	-.186	-.251	-.153
	3 or 4	OWN	SINGLE	SMALL	-.692	-.408	-.739	2.002
				LARGE	1.425	-.304	3.078	-.309
			OTHER	SMALL	-.141	1.171	-.538	.127
				LARGE	-.896	-1.117	.642	-.700
		RENT	SINGLE	SMALL	-.141	.251	-.342	-.480
				LARGE	2.310	-.307	-.412	-.167
			OTHER	SMALL	1.457	-.578	-.625	-.305
				LARGE	-.177	-.201	-.217	-.106
	5 or MORE	OWN	SINGLE	SMALL	-.371	-.469	-.694	-.238
				LARGE	-.261	-.330	-.489	-.168
			OTHER	SMALL	-.858	1.045	-.207	.616
				LARGE	.805	-.449	1.325	-.520
		RENT	SINGLE	SMALL	1.645	-.833	-.914	-.227
				LARGE	-.155	-.273	-.300	-.075
			OTHER	SMALL	-.306	-.746	-.658	-.197
				LARGE	-.100	-.245	-.216	-.065

TABLE VI b

FREEMAN-TUKEY DEVIATES

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	.844	-.489	.589	.004
				LARGE	-.382	-.325	.308	-1.549
			OTHER	SMALL	.377	.191	-2.701	.783
				LARGE	.696	.559	1.707	-1.788
		RENT	SINGLE	SMALL	-1.185	.481	-.298	.972
				LARGE	-.228	-.350	.667	-.650
			OTHER	SMALL	-.097	-.276	-.419	.920
				LARGE	-.014	-.042	-.066	-.080
	3 or 4	OWN	SINGLE	SMALL	-.284	-.728	-.857	1.509
				LARGE	-.058	-.167	-.203	-.311
			OTHER	SMALL	.899	1.092	-1.492	.067
				LARGE	-.112	-.445	-.397	-.350
		RENT	SINGLE	SMALL	-.600	-.064	1.030	-1.512
				LARGE	-.031	-.170	1.296	-.100
			OTHER	SMALL	-.038	-.375	-.179	-.214
				LARGE	-.002	-.017	-.008	-.009
	5 or MORE	OWN	SINGLE	SMALL	-.446	-.301	-.231	.775
				LARGE	1.329	-.055	-.041	-.129
			OTHER	SMALL	.163	-1.211	.670	.269
				LARGE	-.289	-.278	-.154	-.260
		RENT	SINGLE	SMALL	-.665	.628	-.375	-.592
				LARGE	-.031	-.038	-.016	-.027
			OTHER	SMALL	-.080	1.235	-.050	-.121
				LARGE	-.003	-.007	-.002	-.005

TABLE VI b (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12K - 29,999	1 or 2	OWN	SINGLE	SMALL	.717	1.526	-1.419	1.346
				LARGE	-.631	-.561	.847	-.726
			OTHER	SMALL	.186	1.087	-2.583	.749
				LARGE	-.204	-.636	1.674	-1.824
		RENT	SINGLE	SMALL	.729	-2,025	-.641	.358
				LARGE	-.389	.812	.527	-.273
			OTHER	SMALL	-.322	-.845	1.264	-.375
				LARGE	-.069	-.209	1.194	-.082
	3 or 4	OWN	SINGLE	SMALL	-1.957	.010	-1.482	-1.774
				LARGE	-.736	.917	.981	-.655
			OTHER	SMALL	.622	-.329	.348	1.042
				LARGE	.196	-1.006	1.319	-1.588
		RENT	SINGLE	SMALL	.665	1.325	-.290	.568
				LARGE	-.433	-.506	-.749	-.229
			OTHER	SMALL	-.915	-.256	-1.729	.596
				LARGE	-.073	-.160	-.168	-.063
	5 or MORE	OWN	SINGLE	SMALL	.378	.555	.981	.378
				LARGE	-.315	-.253	.826	-.315
			OTHER	SMALL	.284	.418	-1.630	.976
				LARGE	.183	-2.187	.815	-1.337
		RENT	SINGLE	SMALL	-.057	-.547	1.167	-.964
				LARGE	-.121	-.180	-.255	-.070
			OTHER	SMALL	-.538	1.503	.964	-.538
				LARGE	-.034	-.096	-.091	-.034

TABLE VI b (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30k and over	1 or 2	OWN	SINGLE	SMALL	1.033	-.070	-.320	-.169
				LARGE	.768	-.128	-.550	-.301
			OTHER	SMALL	.021	1.383	.203	.672
				LARGE	-.456	-1.231	.305	-1.199
		RENT	SINGLE	SMALL	-.826	-.314	-.745	1.178
				LARGE	-.399	-.139	1.058	-.103
			OTHER	SMALL	1.163	-.156	-.270	-.109
				LARGE	-.110	-.067	-.119	-.046
	3 or 4	OWN	SINGLE	SMALL	-.707	-.290	-.785	1.116
				LARGE	.978	-.170	1.658	-.175
			OTHER	SMALL	-.026	1.076	-.446	.287
				LARGE	-.831	-1.447	.684	-.720
		RENT	SINGLE	SMALL	.047	.306	-.159	-.387
				LARGE	1.167	-.173	-.296	-.054
			OTHER	SMALL	.988	-.529	-.601	-.171
				LARGE	-.061	-.078	-.090	-.022
	5 or MORE	OWN	SINGLE	SMALL	-.245	-.370	-.711	-.108
				LARGE	-.128	-.198	-.398	-.055
			OTHER	SMALL	-.781	1.016	-.124	.631
				LARGE	.788	-.315	1.225	-.442
		RENT	SINGLE	SMALL	1.039	-.943	-1.084	-.098
				LARGE	-.047	-.140	-.166	-.011
			OTHER	SMALL	-.172	-.796	-.654	-.075
				LARGE	-.020	-.114	-.089	-.008

for both sets of data, we will examine one year's set of data using the other year's model. Initially, we will deal with fitting the 1972 model to the 1974 data.

As can be seen from Table VII, the technique utilized to fitting the model is similar to the techniques utilized to fit the previous models. The only difference is that the particular variables utilized in the fitting of the model are based on 1972's data and we are applying them to the 1974 data. On Page 69 (Table VIIb) we note that fitting the model BI, BO, MO, HO, SI and HS results in a likelihood ratio probability that exceeds .05 but a Pearsonian chi-square probability of less than .05 and, thus, for the 1974 data it is shown that the 1972 model does not fit and cannot be utilized to describe the 1974 data.

FITTING THE 1974 MODEL TO THE 1972 DATA

Following the above procedure, Table VIII shows the fitting of the 1974 model to the 1972 data. In this case, after all is taken place, it can be seen that this model does not fit the earlier year's data. Thus, the most parsimonious model for both years is the model that includes BHO, BSI, HS, OS, MO, MS, MI, and HI. This model resulted in a likelihood ratio probability of .9245 and Pearson chi-square probability of .8453 well in excess of the required .05 and, thus, represents a parsimonious and good fit. Thus, it can be stated that

TABLE VII

FITTING THE 1972
MODEL TO THE 1974
DATA

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	1	0	2	2
				LARGE	0	0	1	0
			OTHER	SMALL	1	1	0	4
				LARGE	1	1	5	0
		RENT	SINGLE	SMALL	0	2	3	5
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	0	1
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	0	0	3
				LARGE	0	0	0	0
			OTHER	SMALL	1	3	0	1
				LARGE	0	0	0	0
		RENT	SINGLE	SMALL	0	2	3	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	0	1
				LARGE	1	0	0	0
			OTHER	SMALL	1	0	1	1
				LARGE	0	0	0	0
		RENT	SINGLE	SMALL	0	1	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	0
				LARGE	0	0	0	0

TABLE VII (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	1	2	0	2
				LARGE	0	0	2	0
			OTHER	SMALL	3	6	2	3
				LARGE	2	2	12	0
		RENT	SINGLE	SMALL	2	0	2	1
				LARGE	0	1	1	0
			OTHER	SMALL	0	0	2	0
				LARGE	0	0	1	0
	3 or 4	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	1	2	0
			OTHER	SMALL	13	9	23	8
				LARGE	3	1	9	0
		RENT	SINGLE	SMALL	6	9	8	3
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	1
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	1	1	3	1
				LARGE	0	0	1	0
			OTHER	SMALL	9	11	12	7
				LARGE	2	0	6	0
		RENT	SINGLE	SMALL	1	1	5	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	3	2	0
				LARGE	0	0	0	0

TABLE VII (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30k and over	1 or 2	OWN	SINGLE	SMALL	1	0	0	0
				LARGE	1	0	0	0
			OTHER	SMALL	2	2	2	1
				LARGE	3	0	4	0
		RENT	SINGLE	SMALL	0	0	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	1	0	0	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	0	0	1
				LARGE	1	0	2	0
			OTHER	SMALL	4	4	4	1
				LARGE	1	0	4	0
		RENT	SINGLE	SMALL	1	1	1	0
				LARGE	1	0	0	0
			OTHER	SMALL	1	0	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	1	8	8	1
				LARGE	2	2	7	0
		RENT	SINGLE	SMALL	1	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	0	0
				LARGE	0	0	0	0

TABLE VII a

RESULTS OF FITTING ALL
K-FACTOR MARGINALS

K-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB
1	10	435.63	0.0000	838.17	0.0000
2	40	324.80	0.0000	561.93	0.0000
3	82	80.15	.5373	104.75	.0459
4	91	87.17	.5942	106.28	.1305
5	52	.79	1.0000	.40	1.0000
6	12	.16	1.0000	.08	1.0000

TABLE VIII

FITTING THE 1974 MODEL
TO THE 1972 DATA

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK(B) SAVINGS	COMMERCE	BOTH	NEITHER
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	1	1	3	0
				LARGE	0	0	1	0
			OTHER	SMALL	1	4	1	1
				LARGE	1	0	3	0
		RENT	SINGLE	SMALL	0	2	3	2
				LARGE	0	0	1	0
			OTHER	SMALL	0	1	1	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	1	1	0	0
				LARGE	0	0	2	0
		RENT	SINGLE	SMALL	0	2	5	3
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	1	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	1	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	0	1	1
				LARGE	0	0	0	0
		RENT	SINGLE	SMALL	0	0	0	0
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	1	0
				LARGE	0	0	0	0

TABLE VIII (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	1	1	0	0
				LARGE	0	0	3	0
			OTHER	SMALL	1	7	7	0
				LARGE	1	1	4	0
		RENT	SINGLE	SMALL	1	4	1	1
				LARGE	0	1	2	0
			OTHER	SMALL	0	0	0	1
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	3	0
				LARGE	0	0	0	0
			OTHER	SMALL	5	18	19	5
				LARGE	0	0	9	0
		RENT	SINGLE	SMALL	1	11	12	3
				LARGE	0	0	1	0
			OTHER	SMALL	0	2	0	0
				LARGE	0	0	1	0
	5 or MORE	OWN	SINGLE	SMALL	0	2	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	3	13	17	2
				LARGE	0	1	7	0
		RENT	SINGLE	SMALL	0	1	5	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	3	2	0
				LARGE	0	0	0	0

TABLE VIII (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NEITHER
30k and over	1 or 2	OWN	SINGLE	SMALL	0	1	0	1
				LARGE	0	0	1	0
			OTHER	SMALL	1	3	4	0
				LARGE	1	1	5	0
		RENT	SINGLE	SMALL	1	2	1	0
				LARGE	0	0	1	0
			OTHER	SMALL	0	0	2	0
				LARGE	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	0	2	0
			OTHER	SMALL	1	7	8	2
				LARGE	1	0	10	0
		RENT	SINGLE	SMALL	1	0	3	0
				LARGE	0	1	1	0
			OTHER	SMALL	1	1	0	0
				LARGE	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	1	1	0
				LARGE	0	0	1	0
			OTHER	SMALL	3	6	11	3
				LARGE	1	1	8	0
		RENT	SINGLE	SMALL	1	0	1	1
				LARGE	0	0	0	0
			OTHER	SMALL	0	1	0	1
				LARGE	0	0	0	0

TABLE VIII (a)

RESULTS OF FITTING ALL
K-FACTOR MARGINALS

K-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB.
1	10	511.61	0.0000	1174.84	0.0000
2	40	292.22	0.0000	397.17	0.0000
3	82	65.10	.9147	71.11	.7991
4	91	82.96	.7140	108.00	.1079
5	52	1.18	1.0000	.64	1.0000
6	12	.33	1.0000	.17	1.0000

the 1972 model cannot be used on the 1974 data because of the inconsistency between the likelihood ratio statistic and the Pearson chi-square as noted in Table VII, but the 1974 model can be applied to the 1972 data.

BANK SWITCHING DATA

Previously, our dependent variable for both the 1972 data and the 1974 data was the bank. There were four variables considered within the bank: (1) Only a savings bank account (2) Only a commercial bank account (3) Both a savings and commercial bank accounts and (4) neither type of bank account. The switching model contains five variables that can occur. (1) A change in a savings bank account only, (2) A change in a commercial bank account only, (3) A change in both, (4) No change in any type of bank account and, (5) A switch from savings to commercial or commercial to savings. What we decided to do was take a sub-sample of 240 from the 343 items with regard to the switching characteristic and run similar tests as we did on the 1972-1974 data.

Table IX depicts the saturated table for the 240 depositors represented in this sub-sample. When these data are run, it turns out that once again, there is a large degree of sparseness and by looking at the K factors it appears that a 4th order interaction results in an appropriate likelihood ratio statistic and Pearson chi-square probabilities. This saturated model was fit

TABLE IX

SATURATED SWITCHING MODEL
FOR SAMPLE OF 240

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	0	2	1	0	0
				LARGE	0	0	0	1	0
			OTHER	SMALL	0	2	1	1	0
				LARGE	0	1	0	1	0
		RENT	SINGLE	SMALL	0	1	0	4	0
				LARGE	0	1	0	0	0
			OTHER	SMALL	0	0	0	1	0
				LARGE	0	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	0	0	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	0	2	0
				LARGE	2	0	0	0	0
		RENT	SINGLE	SMALL	0	2	3	3	1
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	1	0	0
				LARGE	0	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	1	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	0	2	0
				LARGE	0	0	0	1	0
		RENT	SINGLE	SMALL	0	0	0	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	1	1	0
				LARGE	0	0	0	0	0

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	0	0	0	1	0
				LARGE	0	1	0	0	0
			OTHER	SMALL	2	4	1	6	1
				LARGE	1	1	1	2	0
		RENT	SINGLE	SMALL	1	1	1	2	1
				LARGE	0	1	1	1	0
			OTHER	SMALL	0	0	0	0	0
				LARGE	0	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	1	2	0	1	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	5	5	7	12	2
				LARGE	0	3	1	1	2
		RENT	SINGLE	SMALL	1	8	2	7	1
				LARGE	0	0	1	0	0
			OTHER	SMALL	0	2	0	0	0
				LARGE	0	0	0	1	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	0	1	1
				LARGE	0	0	0	0	0
			OTHER	SMALL	4	7	1	10	2
				LARGE	2	3	0	1	1
		RENT	SINGLE	SMALL	0	3	1	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	2	0	0	1	0
				LARGE	0	0	0	0	0

TABLE IX (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
30k and over	1 or 2	OWN	SINGLE	SMALL	1	1	0	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	1	2	1	2	0
				LARGE	1	1	0	4	0
		RENT	SINGLE	SMALL	2	1	1	0	0
				LARGE	0	0	0	0	1
			OTHER	SMALL	0	0	0	0	0
				LARGE	0	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	1	0	0
				LARGE	1	0	0	0	0
			OTHER	SMALL	3	0	2	4	1
				LARGE	1	2	1	2	1
		RENT	SINGLE	SMALL	0	2	0	0	0
				LARGE	0	0	0	1	0
			OTHER	SMALL	0	0	0	1	1
				LARGE	0	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	1	0	1	0
				LARGE	0	1	0	0	0
			OTHER	SMALL	1	2	4	3	1
				LARGE	2	2	0	0	2
		RENT	SINGLE	SMALL	1	0	0	2	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	0	1	0
				LARGE	0	0	0	0	0

TABLE IX a

RESULTS OF FITTING ALL
K-FACTOR MARGINALS

K-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB.
1	11	273.36	0.0000	558.00	0.0000
2	47	189.11	0.0000	257.72	0.0000
3	101	101.58	.4650	179.30	.0000
4	116	96.91	.9007	93.39	.9393
5	68	.89	1.0000	.46	1.0000
6	16	.23	1.0000	.12	1.0000

TABLE IX b

FITTING THE SWITCHING MODEL

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	.082	.299	.149	.278	.047
				LARGE	.032	.115	.026	.064	.027
			OTHER	SMALL	.643	.883	.633	1.634	.288
				LARGE	.248	.338	.110	.378	.167
		RENT	SINGLE	SMALL	.286	1.039	.519	.968	.164
				LARGE	.035	.127	.029	.071	.030
			OTHER	SMALL	.070	.096	.069	.178	.031
				LARGE	.009	.012	.004	.013	.006
	3 or 4	OWN	SINGLE	SMALL	.115	.416	.208	.388	.065
				LARGE	.044	.159	.036	.090	.038
			OTHER	SMALL	1.099	1.510	1.083	2.794	.492
				LARGE	.424	.578	.188	.647	.285
		RENT	SINGLE	SMALL	.399	1.448	.723	1.348	.228
				LARGE	.049	.177	.040	.100	.042
			OTHER	SMALL	.120	.165	.118	.305	.054
				LARGE	.015	.020	.007	.023	.010
	5 or MORE	OWN	SINGLE	SMALL	.038	.139	.069	.129	.022
				LARGE	.015	.053	.012	.030	.013
			OTHER	SMALL	.964	1.324	.949	2.450	.432
				LARGE	.372	.507	.165	.567	.250
		RENT	SINGLE	SMALL	.133	.483	.241	.449	.076
				LARGE	.016	.059	.013	.033	.014
			OTHER	SMALL	.105	.145	.104	.268	.047
				LARGE	.013	.018	.006	.020	.009

TABLE IX (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	.302	1.096	.547	1.020	.172
				LARGE	.114	.409	.093	.230	.097
			OTHER	SMALL	2.356	3.237	2.321	5.990	1.056
				LARGE	.886	1.208	.393	1.351	.596
		RENT	SINGLE	SMALL	1.050	3.811	1.903	3.548	.600
				LARGE	.126	.453	.103	.255	.108
			OTHER	SMALL	.257	.354	.253	.654	.115
				LARGE	.031	.042	.014	.047	.021
	3 or 4	OWN	SINGLE	SMALL	.420	1.526	.762	1.421	.240
				LARGE	.158	.570	.129	.321	.136
			OTHER	SMALL	4.030	5.536	3.970	10.246	1.805
				LARGE	1.516	2.066	.673	2.311	1.019
		RENT	SINGLE	SMALL	1.462	5.308	2.650	4.942	.835
				LARGE	.175	.632	.143	.355	.150
			OTHER	SMALL	.440	.605	.434	1.119	.197
				LARGE	.053	.072	.023	.080	.035
	5 or MORE	OWN	SINGLE	SMALL	.140	.509	.254	.474	.080
				LARGE	.053	.190	.043	.107	.045
			OTHER	SMALL	3.534	4.855	3.481	8.985	1.583
				LARGE	1.329	1.812	.590	2.027	.893
		RENT	SINGLE	SMALL	.487	1.769	.883	1.647	.278
				LARGE	.058	.211	.048	.118	.050
			OTHER	SMALL	.386	.530	.380	.981	.173
				LARGE	.046	.063	.021	.071	.031

TABLE IX b (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
30k and over	1 or 2	OWN	SINGLE	SMALL	.123	.448	.224	.417	.071
				LARGE	.104	.376	.085	.212	.090
			OTHER	SMALL	.964	1.324	.949	2.450	.432
				LARGE	.815	1.111	.362	1.243	.548
		RENT	SINGLE	SMALL	.429	1.559	.778	1.451	.245
				LARGE	.116	.417	.095	.235	.099
			OTHER	SMALL	.105	.145	.104	.268	.047
				LARGE	.028	.039	.013	.043	.019
	3 or 4	OWN	SINGLE	SMALL	.172	.624	.312	.581	.098
				LARGE	.145	.524	.119	.295	.125
			OTHER	SMALL	1.649	2.265	1.624	4.191	.739
				LARGE	1.395	1.901	.619	2.126	.937
		RENT	SINGLE	SMALL	.598	2.172	1.084	2.022	.342
				LARGE	.161	.581	.132	.327	.138
			OTHER	SMALL	.180	.247	.177	.458	.081
				LARGE	.049	.066	.022	.074	.033
	5 or MORE	OWN	SINGLE	SMALL	.057	.208	.104	.194	.033
				LARGE	.048	.175	.040	.098	.042
			OTHER	SMALL	1.446	1.986	1.424	3.676	.648
				LARGE	1.223	1.667	.543	1.865	.822
		RENT	SINGLE	SMALL	.199	.724	.361	.674	.114
				LARGE	.054	.194	.044	.109	.046
			OTHER	SMALL	.158	.217	.156	.401	.071
				LARGE	.043	.058	.019	.065	.029

TABLE IX C

STANDARDIZED RESIDUALS

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	-.287	3.112	2.203	-.527	-.217
				LARGE	-.178	-.338	-.161	3.686	-.165
			OTHER	SMALL	-.802	1.189	.461	-.496	-.537
				LARGE	-.498	1.138	-.332	1.011	-.408
		RENT	SINGLE	SMALL	-.535	-.039	-.720	3.083	-.404
				LARGE	-.188	2.450	-.170	-.267	-.174
			OTHER	SMALL	-.265	-.311	-.263	1.945	-.177
				LARGE	-.093	-.109	-.062	-.115	-.076
	3 or 4	OWN	SINGLE	SMALL	-.339	-.645	-.456	-.622	-.256
				LARGE	-.210	-.399	-.190	-.300	-.195
			OTHER	SMALL	-1.048	-1.229	-1.040	-.475	-.702
				LARGE	2.418	-.761	-.434	-.804	-.534
		RENT	SINGLE	SMALL	-.631	.459	2.679	1.423	1.618
				LARGE	-.222	-.421	-.200	-.315	-.205
			OTHER	SMALL	-.346	-.406	2.564	-.552	-.232
				LARGE	-.122	-.142	-.081	-.150	-.100
	5 or MORE	OWN	SINGLE	SMALL	-.195	-.372	3.536	-.359	-.148
				LARGE	-.121	-.231	-.110	-.173	-.112
			OTHER	SMALL	-.982	-1.151	-.974	-.288	-.657
				LARGE	-.610	-.712	-.407	.574	-.500
		RENT	SINGLE	SMALL	-.365	-.695	-.491	-.670	-.276
				LARGE	-.128	-.243	-.116	-.182	-.118
			OTHER	SMALL	-.324	-.380	2.783	1.416	-.217
				LARGE	-.114	-.133	-.076	-.141	-.093

TABLE IX C (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	-.549	-1.047	.740	-.020	-.415
				LARGE	-.337	.924	-.305	-.400	-.312
			OTHER	SMALL	-.232	.424	-.867	.004	-.054
				LARGE	.121	-.189	.967	.558	-.772
		RENT	SINGLE	SMALL	-.049	-1.440	-.654	-.822	.517
				LARGE	-.355	.812	2.798	1.475	-.328
			OTHER	SMALL	-.507	.595	-.503	-.809	-.340
				LARGE	-.176	-.205	-.117	-.217	-.144
	3 or 4	OWN	SINGLE	SMALL	.894	.383	-.873	-.353	-.490
				LARGE	-.398	-.755	-.359	-.566	-.368
			OTHER	SMALL	.483	-.228	1.521	.548	.145
				LARGE	-1.231	.650	.399	-.862	.972
		RENT	SINGLE	SMALL	-.382	1.168	-.399	.926	.180
				LARGE	-.419	-.795	2.264	-.596	-.388
			OTHER	SMALL	-.663	1.794	-.658	-1.058	-.444
				LARGE	-.230	-.268	-.153	3.241	-.188
	5 or MORE	OWN	SINGLE	SMALL	-.374	-.713	-.504	.765	3.251
				LARGE	-.230	-.436	-.208	-.327	-.213
			OTHER	SMALL	.248	.974	-1.330	.339	.331
				LARGE	.582	.883	-.768	-.721	.112
		RENT	SINGLE	SMALL	-.698	.925	.124	-1.283	-.528
				LARGE	-.242	-.459	-.219	-.344	-.224
			OTHER	SMALL	2.598	-.728	-.617	.019	-.416
				LARGE	-.215	-.251	-.143	-.266	-.176

TABLE IX C (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
30k and over	1 or 2	OWN	SINGLE	SMALL	2.494	.824	-.473	-.646	-.266
				LARGE	-.323	-.613	-.292	-.460	-.299
			OTHER	SMALL	.037	.587	.052	-.288	-.657
				LARGE	.205	-.105	-.602	2.473	-.740
		RENT	SINGLE	SMALL	2.397	-.448	.251	-1.205	-.495
				LARGE	-.340	-.646	-.308	-.484	2.859
			OTHER	SMALL	-.324	-.380	-.322	-.517	-.217
				LARGE	.168	-.197	-.112	-.208	-.138
	3 or 4	OWN	SINGLE	SMALL	-.415	.475	1.233	-.762	-.313
				LARGE	2.240	-.724	-.345	-.543	-.353
			OTHER	SMALL	1.053	-1,505	.295	-.093	.304
				LARGE	-.334	.072	.484	-.087	.065
		RENT	SINGLE	SMALL	-.773	-.116	-1,041	-1,422	-.585
				LARGE	-.402	-.762	-.363	1.177	-.372
			OTHER	SMALL	-.424	-.497	-.421	.801	3.237
				LARGE	-.220	-.257	-.147	-.272	-.181
	5 or MORE	OWN	SINGLE	SMALL	-.239	1.736	-.322	1.832	-.181
				LARGE	-.220	1,975	-.199	-.314	-.204
			OTHER	SMALL	-.371	.010	2.159	-.352	.438
				LARGE	.703	.258	-.737	-1.365	1.299
		RENT	SINGLE	SMALL	1.793	-.851	-.601	1.615	-.337
				LARGE	-.232	-.440	-.210	-.330	-.215
			OTHER	SMALL	-.397	-.466	-.394	.945	-.266
				LARGE	-.206	-.241	-.137	-.255	-.169

utilizing the variables CM, CH, HS, MO, MI, and HO where C depicts the term change as a replacement for the term bank (B). The standardized residuals are calculated by a similar manner of taking the observed, substracting the fitted and dividing that quantity by the square root of the fitted values. When that is done, again we note, that basically there is a symmetrical distribution around zero with approximately equal numbers of minuses and pluses. The Freeman-Tukey test shows us that we do have a good fit utilizing these variables. While the saturated data gives rise to a particular model we then, because of the sparseness add a delta factor of .5 as we have done in the other samples and redo the data with regard to finding the particular model that is most appropriate.

In Table X, it shows that a third order interaction would be appropriate. The data causes a degree of concern however, because a comparison of what happened between these years 1972 and 1974 to the depositors represents too good a fit as depicted in Table X. There is a possible instability in the switching data which may be caused by the enormous sparseness. While this thesis is designed to apply new methodology in the field of marketing, these data cause concern about its applicability and may represent some problems. Too good a fit gives this researcher a hesistancy and perhaps future studies with larger sample sizes in order to reduce sparseness could alleviate any

TABLE X

SWITCHING MODEL FOR SAMPLE OF 240
WITH DELTA OF 0.5

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
0 - 11,999	1 or 2	OWN	SINGLE	SMALL	0	2	1	0	0
				LARGE	0	0	0	1	0
			OTHER	SMALL	0	2	1	1	0
				LARGE	0	1	0	1	0
		RENT	SINGLE	SMALL	0	1	0	4	0
				LARGE	0	1	0	0	0
			OTHER	SMALL	0	0	0	1	0
				LARGE	0	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	0	0	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	0	2	0
				LARGE	2	0	0	0	0
		RENT	SINGLE	SMALL	0	2	3	3	1
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	1	0	0
				LARGE	0	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	1	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	0	2	0
				LARGE	0	0	0	1	0
		RENT	SINGLE	SMALL	0	0	0	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	1	1	0
				LARGE	0	0	0	0	0

TABLE X (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
12k - 29,999	1 or 2	OWN	SINGLE	SMALL	0	0	0	1	0
				LARGE	0	1	0	0	0
			OTHER	SMALL	2	4	1	6	1
				LARGE	1	1	1	2	0
		RENT	SINGLE	SMALL	1	1	1	2	1
				LARGE	0	1	1	1	0
			OTHER	SMALL	0	0	0	0	0
				LARGE	0	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	1	2	0	1	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	5	5	7	12	2
				LARGE	0	3	1	1	2
		RENT	SINGLE	SMALL	1	8	2	7	1
				LARGE	0	0	1	0	0
			OTHER	SMALL	0	2	0	0	0
				LARGE	0	0	0	1	0
	5 or MORE	OWN	SINGLE	SMALL	0	0	0	1	1
				LARGE	0	0	0	0	0
			OTHER	SMALL	4	7	1	10	2
				LARGE	2	3	0	1	1
		RENT	SINGLE	SMALL	0	3	1	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	2	0	0	1	0
				LARGE	0	0	0	0	0

TABLE X (Continued)

HHINC (I)	HHLSZ (S)	OWN (O)	HOUSE (H)	TOTMONY (M)	BANK (B) SAVINGS	COMMERCE	BOTH	NON	SWITCH
30k and over	1 or 2	OWN	SINGLE	SMALL	1	1	0	0	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	1	2	1	2	0
				LARGE	1	1	0	4	0
		RENT	SINGLE	SMALL	2	1	1	0	0
				LARGE	0	0	0	0	1
			OTHER	SMALL	0	0	0	0	0
				LARGE	0	0	0	0	0
	3 or 4	OWN	SINGLE	SMALL	0	1	1	0	0
				LARGE	1	0	0	0	0
			OTHER	SMALL	3	0	2	4	1
				LARGE	1	2	1	2	1
		RENT	SINGLE	SMALL	0	2	0	0	0
				LARGE	0	0	0	1	0
			OTHER	SMALL	0	0	0	1	1
				LARGE	0	0	0	0	0
	5 or MORE	OWN	SINGLE	SMALL	0	1	0	1	0
				LARGE	0	1	0	0	0
			OTHER	SMALL	1	2	4	3	1
				LARGE	2	2	0	0	2
		RENT	SINGLE	SMALL	1	0	0	2	0
				LARGE	0	0	0	0	0
			OTHER	SMALL	0	0	0	1	0
				LARGE	0	0	0	0	0

TABLE X a

RESULTS OF FITTING ALL
K-FACTOR MARGINALS

This Is A Simultaneous Test That All k+1 And Higher Factor Interactions Are Zero

K-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB.	ITERATIONS
0 (MEAN)	359	366.88	.3757	622.29	0.0000	
1	348	213.72	1.0000	256.00	.9999	2
2	301	104.19	1.0000	107.78	1.0000	5
3	200	58.13	1.0000	58.91	1.0000	4
4	84	18.05	1.0000	18.09	1.0000	4
5	16	3.71	.9993	3.77	.9993	3

A Simultaneous Test That All K-Factor Interactions Are Zero.

The Entries Are Differences In The Above Table.

K-FACTOR	D.F.	LR CHISQ	PROB.	PEARSON CHISQ	PROB.
1	11	153.16	0.0000	366.28	0.0000
2	47	109.53	.0000	148.22	0.0000
3	101	46.06	1.0000	48.88	1.0000
4	115	40.08	1.0000	40.82	1.0000
5	68	14.34	1.0000	14.32	1.0000
6	16	3.71	.9993	3.77	.9993

doubts about the applicability of this technique.

CHAPTER 4

In Chapter 3 we spent a considerable effort in attempting to fit appropriate parsimonious loglinear models for both the 1972 and 1974 data. While the data were plagued with pockets of extreme sparseness, we were successful in describing them by models with acceptable fit statistics, even though they contain far fewer parameters than what would be needed for a saturated design.

The task at hand is to use the induced models to arrive at rules for allocating observations to the Banking Market Segments previously defined. While the original data contained four groupings - individuals with only savings accounts, those with only commercial accounts, those with both and those with neither, we have, because of sparseness constraints, restricted consideration to the first three.

Recall the variables used in modeling:

<u>Response Variable</u>

"Banks" - Savings
- Commercial
- Both Savings & Commercial

<u>Independent Variables</u>

1) "Household Income" - < \$12,000
- \$12,000 - \$29,999
- > \$30,000

2) "Household Size" - 1 or 2
- 3 or 4
- $\geq$ 5

3) "Ownership" - own

- rent

4) "type of household" - single family

- other

5) "total money" - small depositor

- large depositor

Taking the variables in the order of the above listing, the following variable labels along with their respective running indices have been used:

B; $i = 1,2,3$

I; $j = 1,2,3$

S; $k = 1,2,3$

O; $\ell = 1,2$

H; $m = 1,2$

M; $n = 1,2$

For the 1972 data, the fitted model is,

BI, BO, MO, HO, SI, HS

that is,

$$\ell n\ M_{ijklmn} = U + U_i^B + U_j^I + U_k^S + U_\ell^O + U_m^H + U_n^M + U_{ij}^{BI} + U_{i\ell}^{BO} + U_{\ell n}^{MO} + U_{\ell m}^{HO} + U_{jk}^{SI} + U_{km}^{HS}$$

Our discussion in Chapter 2 on forming logit models when the response variable has more than two levels, shows there are a number of options available to us once appropriate loglinear models have been found. While as a general statement no one procedure is uniformly best, we have decided to look at pairwise logits. Note that since our response variable has 3 levels it would appear that four logit models are needed; however, a little thought shows that once 3 are given the fourth is redundant in the sense that it can be functionally represented by the others. Using the above loglinear model for the 1972 data leads to the following logits:

$$\text{logit}^{(1)}_{jk\ell mn} = \ell n \left(\frac{M_{1jk\ell mn}}{M_{2jk\ell mn}} \right)$$

$$= (U^{B}_{1} - U^{B}_{2}) + (U^{BI}_{1j} - U^{BI}_{2j}) + (U^{BO}_{1\ell} - U^{BO}_{2\ell})$$

$$\text{logit}^{(2)}_{jk\ell mn} = \ell n \left(\frac{M_{1jk\ell mn}}{M_{3jk\ell mn}} \right)$$

$$= (U^{B}_{1} - U^{B}_{3}) + (U^{BI}_{1j} - U^{BI}_{3j}) + (U^{BO}_{1\ell} - U^{BO}_{3\ell})$$

$$\text{logit}^{(3)}_{jk\ell mn} = \ell n \left(\frac{M_{2jk\ell mn}}{M_{3jk\ell mn}} \right)$$

$$= (U^{B}_{2} - U^{B}_{3}) + (U^{BI}_{2j} - U^{BI}_{3j}) + (U^{BO}_{2\ell} - U^{BO}_{3\ell})$$

Table XI

ESTIMATED LOGIT EFFECTS FOR THE

THREE PAIRWISE LOGIT MODELS (1972 DATA)

	Savings vs. Commercial	Savings vs. Both	Commercial vs. Both
	$\text{logit}_{jk\ell m}^{(1)}$	$\text{Logit}_{jk\ell m}^{(2)}$	$\text{logit}_{jk\ell m}^{(3)}$
Constant	-1.264	-1.814	1.498
Income			
< $12,000	+ .177	+ .166	-.011
12,000-29,000	- .512	- .261	.249
> 29,000	+ .335	+ .097	- .238
Ownership			
Own	.305	.161	-.144
Rent	-.305	-.161	+.144

Table XI lists the logit effects for the three models across the levels of the independent variables - household income and ownership. A cursory examination of these effects yields no consistent discernable pattern in the odds for one banking service over the other. However, a number of observations can be made; the odds of an individual choosing a savings bank only as opposed to banking at a commercial bank or banking at both savings and commercial institutions are positive for individuals at the extreme end of the income scales. This is not the case in our model describing the behavior of the odds for a commercial bank over both a savings and commercial institution. Indeed, in this case the odds completely are reversed; this is, however consistent with the first two models. Owning one's home (all other things remaining constant) leads to positive odds of being a savings bank user as opposed to a commercial or, both a savings and commercial bank user. Again, just the reverse conclusion is the case in modeling the odds in favor of a commercial bank relative to subscribing to both a savings and a commercial institution.

Our loglinear/logit modeling, therefore, allows us to segment the banking markets on the basis of the income and ownership variables. Note that more information with respect to the nature of the three banking segments would be available had we decided to start with a more complicated loglinear model. In this case more independent variables would be included, the result of which would be a more elaborate description of how the odds change for one segment to the other. We chose the former approach, however, since a good fitting parsimonious model is more easily understood and in all likelihood would result in as good a decision rule.

Table XII consists of all the parameter estimates for the fitted loglinear model. The relevant estimates and their differences were used to generate the logit effects. We include them here for completeness.

Table XII

LOGLINEAR EFFECT ESTIMATES

OF THE LOGLINEAR PARAMETERS (LAMBDA)

1972 DATA

BANK (B)

SAVINGS	COMMERCIAL	BOTH	NEITHER
-.815	.449	.999	-.633

TOTMONY (M)

SMALL	LARGE
-.787	-.787

HOUSE (H)

SINGLE	OTHER
-.177	.177

OWN (O)

OWN	RENT
.534	-.534

HHLSZ (S)

1 or 2	3 or 4	5 or more
.063	.326	-.389

HHINC (I)

< 11,999	12k -29,000	30k and over
-.687	.565	.122

Table XII (Continued)

OWN (O)	BANK (B) SAVINGS	COMMERCIAL	BOTH	NEITHER
OWN	.252	-.053	.091	-.289
RENT	-.252	.053	-.091	.289

HHINC (I)	BANK (B) SAVINGS	COMMERCIAL	BOTH	NEITHER
< 11,999	.003	-.174	-.163	.334
12k-29,000	-.202	.310	.061	-.169
30k and over	.199	-.136	.102	-.165

OWN (O)	TOTMONY (M) SMALL	LARGE
OWN	-.295	.295
RENT	.295	-.295

OWN (O)	HOUSE (H) SINGLE	OTHER
OWN	-.821	.821
RENT	.821	-.821

HHLSZ (S)	HOUSE (H) SINGLE	OTHER
1 or 2	.247	-.247
3 or 4	.127	-.127
5 or more	-.373	.373

Table XII (Continued)

HHINC (I)	HHLSZ (S) 1 or 2	3 or 4	5 or more
<11,999	.711	-.102	-.608
12k-29,000	-.419	.190	.229
30k and over	-.291	-.088	.379

To investigate whether segments are constant or change over time, it is necessary to see how the decision rules derived for the 1972 data do for the 1974 data. Unfortunately, the model derived for 1972 does not provide an acceptable fit for 1974. Indeed, as we saw in chapter 3 a much more complicated design was required to adequately describe the nature of the observations.

Recall that the loglinear model that was best to describe the 1974 data is,

BHO, BSI, HS, OS, MO, MS, MI, HI

that is,

$$\ell n_{ijk\ell mn} = U + U_i^B + U_j^I + U_k^S + U_\ell^O + U_m^H + U_n^M + U_{i\ell}^{BO} + U_{im}^{BH} + U_{im}^{BS} + U_{ij}^{BI} + U_{\ell m}^{HO} + U_{jk}^{SI} + U_{km}^{HS} + U_{k\ell}^{OS} + U_{\ell m}^{OM} + U_{kn}^{MS} + U_{jn}^{MI} + U_{jm}^{HI} + U_{i\ell m}^{BHO} + U_{ijk}^{BSI}$$

the corresponding three pairwise logit models are then easily seen to be,

$$\text{logit}^{(1)}_{jk\ell mn} = \ell n\left(\frac{M_{1jk\ell mn}}{M_{2jk\ell mn}}\right)$$

$$= (U_1^{B} - U_2^{B}) + (U_{1\ell}^{BO} - U_{2\ell}^{BO}) + (U_{1m}^{BH} - U_{2m}^{BH})$$

$$+ (U_{1k}^{BS} - U_{2k}^{BS}) + (U_{1j}^{BI} - U_{2j}^{BI}) + (U_{1\ell m}^{BHO} - U_{2\ell m}^{BHO})$$

$$+ (U_{1jk}^{BSI} - U_{2jk}^{BSI}).$$

$$\text{logit}_{jk\ell mn}^{(2)} = \ln\left(\frac{M_{1jk\ell mn}}{M_{2jk\ell mn}}\right)$$

$$= (U_1^{B} - U_3^{B}) + (U_{1\ell}^{BO} - U_{3\ell}^{BO}) + (U_{1m}^{BH} - U_{3m}^{BH})$$

$$+ (U_{1k}^{BS} - U_{3k}^{BS}) + (U_{1j}^{BI} - U_{3j}^{BI}) + (U_{1\ell m}^{BHO} - U_{3\ell m}^{BHO})$$

$$+ (U_{1jk}^{BSI} - U_{3jk}^{BSI}).$$

$$\text{logit}_{jk\ell mn}^{(3)} = \ln\left(\frac{M_{2jk\ell mn}}{M_{3jk\ell mn}}\right)$$

$$= (U_2^{B} - U_3^{B}) + (U_{2\ell}^{BO} - U_{3\ell}^{BO}) + (U_{2m}^{BH} - U_{3m}^{BH})$$

$$+ (U_{2k}^{BS} - U_{3k}^{BS}) + (U_{2j}^{BI} - U_{3j}^{BI}) + (U_{2\ell m}^{BHO} - U_{3\ell m}^{BHO})$$

$$+ (U_{2jk}^{BSI} - U_{3jk}^{BSI}).$$

Table XIII shows the logit effects for the three pair-wise models. We note that the effect estimates are far more elaborate than those for the 1972 data. The most obvious complication is that the logit models here contain interaction terms; this is not the case for the logit models derived for 1972.

Table XIII

ESTIMATED LOGIT EFFECTS FOR THE

THREE PAIRWISE LOGIT MODELS (1974 DATA)

	Savings vs. Commercial	Savings vs. Both	Commercial vs. Both
Constant	-.284	-.700	-.416
Income			
< 12,000	-.473	-.037	+.436
12,000-29,000	-.021	-.165	-.144
> 29,000	+.494	+.201	-.293
Ownership			
Own	+.393	.070	-.323
Rent	-.393	-.070	+.323
Housetype			
Single	-.264	+.069	-.195
Other	+.264	-.069	+.195
HHSZE			
1 or 2	+.409	-.095	-.504
3 or 4	-.173	-.091	+.082
> 5	-.235	+.066	+.421

Table XIII(Continued

ESTIMATED LOGIT EFFECTS FOR THE

THREE PAIRWISE LOGIT MODELS (1974 DATA)

	Savings vs. Commercial	Savings vs. Both	Commercial vs. Both
Housetype by Ownership			
Own x Single	-.059	+.022	-.037
Own x Other	+.059	-.022	+.037
Rent x Single	+.059	-.022	+.037
Rent x Other	-.059	+.022	-.037
Income by Housesize			
< 12,000 x 1 or 2	-.064	-.600	-.539
< 12,000 x 3 or 4	-.789	-.603	+.183
< 12,000 x >,5	+.850	+1.203	+.353
12,000 - 29,000 x 1 or 2	-.655	-.090	+.349
12,000 - 29,000 x 3 or 4	+.364	+.249	-.115
12,000 - 29,000 x ≥5	+.191	-.159	-.350
≥ 30 x 1 or 2	+.618	+.690	+.072
≥ 30 x 3 or 4	+.423	+.354	-.069
≥ 30 x ≥ 5	-1.041	-1.044	-.003

The first observation we made is that restricting attention to income and ownership leads to no authoritative conclusion with respect to the stability in banking segments over time. Focusing attention on only the ownership variable and keeping everything else constant, the pattern in the odds is identical with what happened in 1972. However, in considering household income for 1972, there is a positive contribution to the odds favoring a savings bank for lower income households; there is a marked shift in 1974 to a negative contribution. This is an interesting development which may have a logical explanation; we are, however, not in a position to discuss why this has occurred.

Two additional independent variables are required in the logit models for these data - housetype and household size. There is a consistent pattern across all three logit models for the household size variable in the sense that the odds are monotone within a logit as household size increases from 1 or 2 to greater than or equal to 5. In particular, the odds on being a savings bank user only, to a commercial bank user only, decreases as household size increases. On the other hand, comparing the odds for savings only to both types we see a monotone increase in the odds as household size increases. Lastly, the odds for commercial only relative to both types increases as household size increases.

We remind the reader that segment stability between 1972 and 1974 using the approach we have chosen cannot be adequately analyzed using the housetype and household size variables since these variables are not included in the 1972 logits. Had we done modeling retrospectively by applying the 1974 model to the 1972 data then segmentation analysis on the basis of the four independent variables could proceed.

Continuing our discussion of the logit effects given in Table XIII we now look for patterns in the interaction effects making up the logits. There are four components which comprise the logit effects for the housetype by ownership interaction. The effects are, however, quite small and any attempt to read much into them would potentially be misleading. The income by housesize interaction effects on the other hand, appear to be sizeable and interesting in their pattern. The odds on being a savings depositor, as reflected in the first two columns of Table XIII, show a dramatic drop when we fix the housesize at greater than or equal to 5 and increase the income level from under $12,000 per year to over $30,000. The reverse pattern prevails when the household size is fixed at three or four. For household size fixed at one or two, no monotone pattern in the odds was discernable. Lastly, the third column of Table XIII shows a monotone pattern in the odds favoring a commercial account only to "both" types of accounts when housesize increases; the odds increase for lower income depositors and decrease for the $12,000-$29,000 group.

Table XIV

LOGLINEAR EFFECT ESTIMATES

OF THE LOG-LINEAR PARAMETERS (LAMBDA)
1974 DATA

BANK (B)

SAVINGS	COMMERCIAL	BOTH	NEITHER
-.210	.074	.490	-.355

TOTMONY (M)

SMALL	LARGE
.803	-.803

HOUSE (H)

SINGLE	OTHER
-.051	.051

OWN (O)

OWN	RENT
.804	-.804

HHLSZ (S)

1 or 2	3 or 4	5 or more
.293	.167	-.461

HHINC (I)

< 11,999	12k-29,000	30k and over
-.652	.898	-.245

Table XIV (Continued)

HOUSE (H)	BANK (B) SAVINGS	COMMERCIAL	BOTH	NEITHER
SINGLE	.085	-.179	.016	.079
OTHER	-.085	.179	-.016	-.079

OWN (O)	BANK (B) SAVINGS	COMMERCIAL	BOTH	NEITHER
OWN	.114	-.279	.044	.120
RENT	-.114	.279	-.044	-.120

HHLSZ (S)	BANK (B) SAVINGS	COMMERCIAL	BOTH	NEITHER
1 or 2	.024	-.385	.119	.242
3 or 4	-.084	.089	.007	-.012
5 or more	.060	.295	-.126	-.229

HHINC (I)	BANK (B) SAVINGS	COMMERCIAL	BOTH	NEITHER
< 11,999	-.429	.044	-.392	.778
12k-29,000	-.014	.007	.151	-.144
30k and over	.443	-.051	.242	-.634

OWN (O)	TOTMONY (M) SMALL	LARGE
OWN	-.381	.381
RENT	.381	-.381

Table XIV (Continued)

HHLSZ (S)	TOTMONY (M) SMALL	LARGE
1 or 2	-.427	.427
3 or 4	.185	-.185
5 or more	.242	-.242

HHINC (I)	TOTMONY (M) SMALL	LARGE
< 11,999	.245	-.245
12k-29,000	.067	-.067
30k and over	-.312	.312

OWN (O)	HOUSE (H) SINGLE	OTHER
OWN	-.826	.826
RENT	.826	-.826

HHLSZ (S)	HOUSE (H) SINGLE	OTHER
1 or 2	.079	-.079
3 or 4	.116	-.116
5 or more	-.196	.196

HHINC (I)	HOUSE (H) SINGLE	OTHER
< 11,999	.426	-.426
12k - 29,000	-.100	.100
30k and over	-.326	.326

Table XIV (Continued)

HHLSZ (S)	OWN (O)	
	OWN	RENT
1 or 2	-.088	.088
3 or 4	-.054	.054
5 or more	.143	-.143

HHINC (I)	HHLSZ (S)		
	1 or 2	3 or 4	5 or more
< 11,999	.713	-.332	-.381
12k-29,000	-.377	.232	.145
30k and over	-.366	.100	.236

OWN (O)	HOUSE (H)	BANK (B)			
		SAVINGS	COMMERCIAL	BOTH	NEITHER
OWN	SINGLE	-.095	-.036	-.058	.189
	OTHER	.095	.036	.058	-.189
RENT	SINGLE	.095	.036	.058	-.189
	OTHER	-.095	-.036	-.058	.189

HHINC (I)	HHLSZ (S)	BANK (B)			
		SAVINGS	COMMERCIAL	BOTH	NEITHER
<11,999	1 or 2	-.225	-.161	.375	.011
	3 or 4	-.444	.342	.159	-.057
	5 or more	.669	-.181	-.534	.046
12k - 29,000	1 or 2	-.148	.407	-.058	-.201
	3 or 4	.210	-.154	-.039	-.017
	5 or more	-.062	-.253	.097	.218
30k and over	1 or 2	.373	-.245	-.317	.189
	3 or 4	.234	-.189	-.120	.074
	5 or more	-.607	.434	.437	-.264

Our discussion thus far has been restricted to an analysis of the components comprising the various logit models. We must keep in mind, however, that the actual segments are formed through summing effects determined by which levels of the variables we wish to consider. Recall from Chapter two that a reasonable rule for allocating an observation between a savings only depositor and a commercial only depositor is:

Allocate to savings only if and only if

$$\text{logit}^{(1)}_{jk\ell mn} \geq 0.$$

Similarly, differentiation between savings only and both types of depositors is:

Savings only if and only if

$$\text{logit}^{(2)}_{jk\ell mn} \geq 0.$$

Differentiation between the three segments simultaneously can be accomplished by summing appropriate logits. For example, allocation into the savings only segment can be done by requiring

$$\text{logit}^{(1)}_{jk\ell mn} + \text{logit}^{(2)}_{jk\ell mn} \geq 0.$$

Note this is somewhat less restricted than requiring

$$\ell n \ M_{1jk\ell mn} = \max\ (\ell n\ U_{2jk\ell mn},\ \ell n\ U_{3jk\ell mn})$$

One of the very useful and interesting aspects to the loglinear/logit approach to segmentation is the ability to closely examine the magnitude and sign of the logit effects which ultimately form the allocation rule. This is what we have chosen to spend most of our time upon. Such close examination permits the researcher to profile important components which, in the final analysis, leads to a better understanding of market segments.

One of our principal objectives in this study was to see how the three banking segments changed over the two periods 1972 and 1974. While we had a modicum of success, we were unable to go as far as we would have liked. The problem occurred, as we have discussed, because the models needed to describe the 1972 data and the 1974 data are very different. However, this is interesting in its own right since we are alerted to the fact that the relationship between the explanatory and response variables have changed over the two periods. There are a number of approaches that we can attempt to get more information about significant changes. We might, for example, fit the 1974 model to the 1972 data and examine the constituent logit effects for both periods; major differences would point to changes in the segments. Further, we might start with a third data set involving only those individuals who switched from one kind of a state to another. While this is sensible to do, we would need a richer data base to start with.

In Chapter 3 we fitted a loglinear model to a data set dealing with switches but have not proceeded here with the corresponding logit analysis since we believe that the fit obtained was artificial and of dubious credibility. We do believe, however, that this approach is sensible for uncovering possible segment changes over a two period panel study. The author intends to pursue both approaches at a future time.

CHAPTER 5

SUMMARY AND AREAS OF FUTURE RESEARCH

We have attempted to use the loglinear/logit model in the marketing segmentation problem for multiple segments and changes in possible segments over time. This was our objective. We did not anticipate, nor desire to test the data base used, but, only to show how the statistical techniques can be applied to a data base. As it turns out, while limited conclusions can be made and certainly it appears that this is a viable technique for future usage, the conclusions that can be reached are not as meaningful as we had hoped they would be. The major reason for this was the sparseness of the data. Because of the many cells that contained very few frequencies we were left with conclusions that could not be viewed as significant. Our future choice is to either expand the particular data base from the number of panel members or to apply the techniques to a different data base which contains a greater mass of data. It does remain that these techniques have an advantage over the standard discriminant analysis techniques because these techniques have been derived specifically for this kind of frequency or count data.

Some interesting developments did come to light. For example, when considering the household income for 1972 there is a positive contribution to the odds favoring a savings bank for lower income households; while in 1974 this shifts to a negative contribution. There probably is some logical explanation for this interesting development.

However, based upon our particular data we are not in a position to discuss why it happened. Furthermore, we found that two additional independent variables were required in the logit models for the 1974 data. Since these variables were not included in the 1972 logits, we cannot adequately analyze segment stability between 1972 and 1974. Had we been able to model retrospectively, applying the 1974 model to the 1972 data, then segmentation analysis on the basis of the four independent variables would have occurred. As noted previously, one of our principle objectives was to use the model in order to predict the change in three banking segments over the two periods of time. With this we had a modicum of success but were unable to go as far as we had desired. Again, the problem occurred because the models needed to describe the 1972 data and the 1974 data are very different. This is an interesting situation in its own right because it alerts us to the fact that the relationship between the explanatory and response variables must have changed over the two periods. In order to attempt to get more information about significant changes we might fit the 1974 model to the 1972 data and examine the constituent logit effects for both periods or, we might start with a third data set involving only those individuals who switched from one kind of a state to another. However, again, this would require a richer data base at the outset.

In conclusion, while there appears to be some significant results shown by applying the loglinear/logit approach to this particular data base, the results have been less than conclusive. This now appears to be mainly due to the sparseness of the data and does not alter the belief originally stated that these statistical techniques can be used appropriately in market segmentation research. In addition, while we fitted a loglinear model to a data set dealing with switches, since the fit obtained was artificial and of dubious credibility, we did not proceed with the logit analysis. However, we do believe that this approach is sensible for uncovering possible segment changes over a two period panel study. Future research should be in the areas of less sparse data or a different data base, applying logit analysis to the switching data for this new data base and as was mentioned in Chapter One, the possible use of psychographic characteristics. As noted previously, there is some dissatisfaction with the use of socio-economic characteristics as a basis for predicting the membership of consumers in particular market segment groups and there may be a desire for a constrast of the relative efficacy of socio-economic and psychological characteristics. However, it must be reiterated that the purpose of this thesis was to investigate the statistical techniques of logit and loglinear analysis as a predictor of segment membership over time and, thus, there is no need to delve into a discussion as to the appropriateness of the data base utilized.

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