Title

Patterns of Household Usage of Financial Services: An Analysis from the 1983 and 1986 Surveys of Consumer Finances

Authors

Carman, James M.
Balderston, Frederick E.

Publication Date

1992-11-01

Peer reviewed

iber Institute of Business and Economic Research

University of California at Berkeley

CENTER FOR REAL ESTATE AND URBAN ECONOMICS

WORKING PAPER SERIES

WORKING PAPER NO. 93-214

PATTERNS OF HOUSEHOLD USAGE OF FINANCIAL SERVICES: AN ANALYSIS FROM THE 1983 AND 1986 SURVEYS OF CONSUMER FINANCES

By

JAMES M. CARMAN

FREDERICK E. BALDERSTON

WALTER A. HAAS SCHOOL OF BUSINESS

CENTER FOR REAL ESTATE AND URBAN ECONOMICS
UNIVERSITY OF CALIFORNIA AT BERKELEY
Kenneth Rosen, Chair

The Center was established in 1950 to examine in depth a series of major changes and issues involving urban land and real estate markets. The Center is supported by both private contributions from industry sources and by appropriations allocated from the Real Estate Education and Research Fund of the State of California.

INSTITUTE OF BUSINESS AND ECONOMIC RESEARCH
Richard Sutch, Director

The Institute of Business and Economic Research is an organized research unit of the University of California at Berkeley. It exists to promote research in business and economics by University faculty. These working papers are issued to disseminate research results to other scholars. The authors welcome comments; inquiries may be directed to the author in care of the Center.

PATTERNS OF HOUSEHOLD USAGE OF FINANCIAL SERVICES: AN ANALYSIS FROM THE 1983 AND 1986 SURVEYS OF CONSUMER FINANCES

by

James M. Carman

and

Frederick E. Balderston

Working Paper No. 93-214

November 1992

The authors are Professors of Business Administration in the Walter A. Haas School of Business, University of California, Berkeley. Partial support for this project was provided by the Center for Real Estate and Urban Economics at Berkeley. The authors have benefitted very substantially from the extensive research assistance of Ravi Dhar, now of Yale University, in the analyses upon which this paper is based. They also acknowledge the earlier research assistance of Chand Samaratunga in exploratory data analysis and Torgeir Vaage with a later part of the work.

ABSTRACT

An increasingly large array of financial services is available to US households. Which of these will be desired, and from what institutional sources, depends on such factors as the household's total amount of financial assets and annual income; age, marital status, education and other socio-demographic characteristics; and attitudes toward risk. Among the phenomena to be investigated was the possibility that households of a given type might respond to "cross-selling" of financial services by a given type of vendor.

The authors used the 1983 Survey of Consumer Finances and the re-interview Survey of 1986 to undertake analysis of the segments or clusters of households in the market for financial services. Two algorithms of standard cluster analysis were supplemented by use of the method of Classification and Regression Trees (CART) to test the validity of the clusters that were derived from the financial variables.

Once clusters were identified, economic, demographic and attitudinal correlates were investigated. Each 1983 and 1986 cluster profile is reported.

Because the 1986 sample consisted mainly of reinterviews of 1983 survey households, it was also possible to examine the "cluster-switching" behavior of households. 1983 clusters varied in their stability of carryover to 1986. When households did switch, it was not because they changed differentially on the measured characteristics. Instead, some switchers were already somewhat different in 1983 from other households in the same cluster; others

had significant changes in financial portfolio between the two years which brought about a switch in cluster membership.

Several implications of the findings for marketing management are discussed. These include the identification of clusters of households most promising for sophisticated financial products, as against mass-marketed products.

INTRODUCTION

Changing patterns of usage of financial services by US households depend upon numerous characteristics of these households and upon changing characteristics within the financial services industries, their technologies of operation, and their modes of organization. The 1983 and 1986 Surveys of Consumer Finances, sponsored by the Board of Governors of the Federal Reserve System, offer a unique opportunity to study the nature of these changes in usage and the reasons for them.

The 1980's saw a continuation of tensions at the market boundaries of various financial subindustries, with increasing attempts at cross-penetration of financial-services markets. Financial deregulation in the early 1980's facilitated cross-penetration and made it urgent from both the business and the public policy standpoints to understand whether US households would now respond in new ways to the many competing offers of consumer financial services. Suppliers of these services sometimes offered them in new combinations, and it appeared likely that some categories of households might respond favorably to these new efforts of cross-selling, whereas others would not. Cross-selling not only proved to be an efficient marketing approach, but in addition, a customer receiving multiple services from a single seller is likely to perceive greater switching costs than those with more simple transaction patterns. The result was greater customer loyalty.

The purpose of the research reported here was to better understand how consumers perceive financial services in terms of the variety of investment products available. If cross-selling is the path to successful marketing of financial services, then sellers will need to build relationships with their customers (Berry, 1979). However, relationship marketing is not cheap. Relationship marketing may not be cost effective in all market segments. What is required is a carefully selected and sequenced mix of mass marketing, direct marketing, personal selling, and micromarketing. This mix will be different for each market segment. Market segmentation must consider the demand-side responses to cross-selling efforts by sellers. How can the market be segmented to achieve cost effectiveness? Are age and average balance sufficient segmentation variables (Burnett and Wilkes 1985)? What other factors should be used to construct market segments?

The aim of this research was: to build product market segments based on the balance sheet portfolios of households; then to see how these portfolios are correlated with wealth, income, life cycle, demographic factors, and attitudes toward saving, investing and borrowing; then to see if these factors would help in understanding the changes in household portfolios that occurred between 1982 and 1985; finally, to suggest the marketing implications that flow from this analysis.

The paper is organized into five main section following this introduction. The next section contains a brief review of literature on the subject. This is followed by a section on the data and another on the statistical methodology employed. The fourth section, which comprises the bulk of the paper, reports the findings. The fifth section discusses the managerial implications.

LITERATURE REVIEW

Perhaps the literature that comes closest to addressing the questions addressed in this research is concerned with the hypothesis that households acquire investment products in some logical pattern over their life cycle (Yaegel, 1987). Put more generally, the balance sheets of households should differ predictably over the life cycle. Young families may have negative net worth and take on substantial debt for higher education, automobiles, household durables, and beginning a family at a time when their incomes are relatively low. Yet, favorable transaction experience with a financial institution can create a favorable predisposition to purchase debt products. Then, as children and incomes grow, the balance sheet shifts and life insurance and growth investments begin to appear. A seller of financial services should be successful in selling such investment products to a family who has had a positive borrowing experience with the institution. Finally, in later years the household has a positive net worth that is likely to be invested in income-producing investments in anticipation of retirement.

Stafford, Kasulis and Lusch (1982) did the first substantial investigation of this hypothesis using a 1975-76 sample of 2,600 households in the Oklahoma City MSA. Very low income households were not sampled. The pattern of financial asset acquisition was fairly uniform for all age levels and followed a pattern of checking account husband's life insurance savings account wife's life insurance stocks bonds trusts mutual funds. Dickinson and Kirzner (1986) replicated this study in a national Canadian, upscale sample of 9,173 families. Both studies used age as their measure of life cycle stage. There were only a few differences from the Oklahoma City sample: the Canadians opened saving accounts before they bought life insurance; they opened an RRSP (Canadian IRA) account before going to other forms of investments; they purchased savings bonds and CDs before they purchased stocks; they purchased mutual funds before corporate bonds. Indeed, one might suspect that this ordering is more like the US as a whole than was the Oklahoma City ordering. With regard to differences among age groups, almost twice the over age 50 families had RRSP accounts as did younger families. These studies validate experience and logic as to the order in which financial assets are acquired.

Kamakura, Ramaswami, and Srivastava (1991) investigated a more intricate relationship to help in developing cross-selling strategies. Borrowing and investing objectives of consumers clearly are correlated with life cycle and wealth. These objectives are used by most investment advisors in recommending a pyramid portfolio with a base of risk management and emergency products such as life insurance and CDs, followed by inflation protecting growth products such as blue-chip stocks and mutual funds, and topped with higher risk and tax-sheltered products. Such a hierarchy suggests that investors learn more about financial products as wealth increases, but education and inherited wealth may allow some consumers to become sophisticated at a relatively young age. These researchers, therefore, developed a measure of "financial maturity" that they used to correlate with the kinds of products found in financial portfolios. This measure was expressed as a logit formulation of the probability that an investor owns a particular financial product.

They tested this formulation using a sample of 3,034 upscale households in the continental United States. Multiple regression analysis of demographic and investment objectives against the financial maturity measure produced an R^2 of .35 with income, net worth, age, education, professional occupation, and home ownership as significant economic-demographic predictors. This study does help a seller of financial services to construct a mix of products to offer to consumers at various stages of financial maturity, but it does less well in helping to identify target segments.

The present study, therefore, used as a starting point for analysis the presumption that US households may be separable into a series of market segments, constructed on the different compositions of financial portfolios they hold (Kinnaird, Shaughnessy, Struman and Swinyard, 1984). The various consumer segments can then be shown to use financial services and institutions according to different patterns, and such usage, while driven mainly by economic characteristics, may be strongly affected by demographic, familiarity, sophistication and attitudinal variables. Note that it is hypothesized age or life cycle are not the only important variables. For example, a household with inherited wealth may hold a similar portfolio be they age forty or seventy.

The hypothesized model of household market segments is shown in Figure 1. The logic of the analysis follows in the tradition of an "aggregation approach" to segmentation. The literature on normative market segmentation suggests that cluster analysis may be useful for aggregating consumers into optimal segments (Mahajan and Jain, 1978; Tollefson and Lessig, 1978; Elrod and Winer, 1982). This approach first clusters the subjects in the sample based on their financial behavior, i.e., their transaction banking, saving, investing, and borrowing behaviors. Then economic, demographic, and attitudinal variables are descriptors of the members of each segment.

THE DATA

The 1983 Survey of Consumer Finances captured data on calendar 1982 financial behavior patterns for 4,262 households, although the usable size of this sample for analysis was approximately 3,900 households. The basic results of the 1983 Survey are reported in Avery, Elliehausen, Canner and Gustafson (1984A, 1984B).

The second, 1986, survey reinterviewed those 1983 respondents who were available in 1986. Relatively complete data on 2,822 households were obtained in both years, and it is this number that was used in the longitudinal analysis reported here. While the 1986 questionnaire obtained less detailed household balance sheet data, sufficient information was collected to enable analysts to compute savings behavior of households in both years. Changes in households' balance sheet holdings in the major categories of assets and liabilities could also be computed.

Employment information was obtained to update the work history of income-earners of the households in the Survey. In addition, the 1986 Survey opened new lines of inquiry to explore the broad role of the family in economic behavior. Consequences of the death of a spouse could be shown, as could the impact of divorce or separation. The Survey followed both parties in cases of divorce or separation.

These two Surveys also solicited information concerning behavioral and attitudinal variables. It was hypothesized that this information could be coupled with financial data and demographic information from the same households to enable an interpretation of the systematic differences in usage of financial services between 1983 and 1986.

US households are characterized by a skewed distribution of incomes and expenditures and a still more skewed distribution of assets and liabilities. The 1983 sample was based on an area sample plus a special high-income sample. With appropriate weighting, the 1983 sample could be used to project the characteristics of the population. In the work reported here, the primary focus was on the characteristics of particular segments. However, the importance of a segment in the population also is of interest. The 1983 sample weights had been adjusted for nonresponse and missing data. The weights used for this purpose were designed to allow the sample of households reached in 1986 to represent the entire 1983 sample.

In as far as the 1983 weights correctly represent the 1983 population, the weighting that was used here approximates the importance of a cluster in 1983, not 1986. As a prime objective of this research was to identify changes in patterns of usage, attention was concentrated upon those 2,822 households for which both 1986 and 1983 data were available. This subset consisted of approximately 64% of the full 1983 sample. Thus the 1986 sample is not representative, even with appropriate weights, of the 1986 population.

In addition, the weight had to be adjusted to account for the separation of families during the three years and the overweighting of the high-income sample. The sample by 1986 excludes immigrants and under-represents persons under age 30 who in 1983 were not living in households (students, military, etc.). For further evidence concerning the reasons for this reduction of sample size and the weighting schema used, see our Appendix Table 1, "Sample Attrition," taken from the Federal Reserve Board's Code Book for 1986.

STATISTICAL METHODOLOGY

Cluster Analysis

As suggested in Figure 1, the statistical investigation began with a cluster analysis of the households based only on the structure of their household balance sheets, i.e., the investing and borrowing products they held in their portfolios. The purpose of this step was to form market segments based on financial behavior. The next step was then to see if these segments could be correlated with: demographic characteristics, income and similar economic variables, attitudinal variables concerning saving, investing, and borrowing. Of particular interest was the way in which the segments and their economic and demographic predictors changed over the three-year period from 1983 to 1986.

The cluster analysis employed the Ward's and FASTCLUS procedures for cluster analysis in the standard Statistical

Analysis System (SAS, 1989). Financial variables used to construct the 1986 and 1983 clusters were:

Variable No.		Description of Variable
1986	1983	
C1405	C1406	$ in checking and savings accounts
C1407	C1408	$ in Keogh and IRA accounts
C1409	C1410	$ in money market accounts and CDs.
C1403	C1404	$ in bonds: savings, government, municipal, corporate
C1401	C1402	$ in stocks and mutual funds
C1413	C1414	$ cash value of whole life insurance
C1415	C1416	$ value, other financial assets (includes trusts, managed investment accounts, personal notes, land contracts, etc.)
C1419	C1420	$ value of business owned
C1512	C1513	$ value of home if it were sold today
C1427	C1428	$ credit card debt
C1525	C1526	$ total home mortgages on primary home.

Because the Survey of Consumer Finances oversampled a special high-income subsample, the cluster procedure was divided into two parts, the main sample (called Stage 1) and the high income sample (called Stage 2).

Outlying observations can have strong effects in cluster analysis. The analysis was carried out on standardized variables (mean = 0; standard deviation = 1) in order to deflate differences in absolute size of means and differences in variance. The initial analyses included only those households that were within the 90th percentile on each of the financial variables used for clustering. This was necessitated by the fact that the sample had a heavily skewed distribution with a long upper tail. Other break points were tested before choosing 90 per cent. Stage 2 of the cluster analysis dealt with those households that had been excluded from Stage 1, and it thus concentrated attention upon the high-income, high net worth households. (In earlier exploratory data analysis, other, more judgmental, methods of dealing with the over-sampling of high income households were explored, but the judgmental approach appeared less satisfactory than the shift to a two-stage clustering procedure.)

The FASTCLUS procedure, on the 1983 data, produced 12 financial portfolio clusters, plus outliers, for the stage 1 sample and 4 clusters plus outliers for the stage 2, high income cluster. But how does one know whether these clusters are robust and make sense in terms of the expected theoretical homogeneity? Do they have nomological validity? Some test of validity and robustness is required. The strategies for accomplishing this are at least four: use a holdout sample; use a jackknife approach to test various subsamples; use other methods of cluster analysis; test if another method of analysis will place households in the correct cluster; reconfigure the data in some way. All except the jackknife approach were used here.

FASTCLUS was used as a first pass because it is efficient in terms of machine time and provided a way to establish the approximate dimensionality of the problem, but Ward's cluster method was the primary clustering algorithm. It employs a different approach than FASTCLUS and is relatively middle-of-the-road in terms of the statistical logic of the various clustering methods.

Outliers from the Ward's method for 1983 became the holdout sample. This reduced, "well-behaved" sample showed that the 12 cluster solution was best on a variety of criteria. Then, variable 1526, total value of home mortgages, (in standardized form) was added to the variables used in the cluster analysis, and the Ward's method was again used on the stage 1 sample. Again, a very reasonable 12 cluster solution emerged.

The FASTCLUS procedure was used to cluster all of the variables, including the holdout sample, and the results of this analysis were compared to the Ward's solution. This time, the Ward result and the FASTCLUS result were more similar. The results mirrored the Ward's results for six of the twelve clusters, but broke or combined other of the FASTCLUS clusters. There was agreement between the two methods for 80% of the cases. The remaining 20% were assigned to their Ward's cluster.

The next step was to compare the Ward's and FASTCLUS solutions for the Stage 2 sample. No holdout sample was employed, but the solutions, using different numbers of clusters, were compared using both methods. A three-cluster Ward's solution produced excellent results with 12 outliers removed. The four-cluster FASTCLUS solution placed 11 of these 12 into a single cluster, so the four cluster solution was accepted at this point. In all, there was agreement between the two methods for 93% of the cases. The remaining 83 cases were assigned to their Ward's cluster.

The 1986 clustering followed a similar procedure. Solutions proved to be more robust when the home mortgage value variable was added. The Ward's solutions were well behaved when only 9 outliers were removed. The 12 cluster FASTCLUS procedure placed 8 of these 9 into a single, unique cluster. Therefore as for 1983, the 12 cluster, stage 1 solution was selected. However, only 74% of the 1708 total cases matched perfectly across the two methods. Assignment of the other cases here was done more carefully with the FASTCLUS assignments sometimes chosen over the Ward's assignment where the fit appeared qualitatively to be more logical.

For 1986 Stage 2, a three-cluster FASTCLUS solution emerged; the Ward's method produced five clusters. The five-cluster solution was selected at this point. However, there was agreement between the two methods for only 31% of the cases.

A final and very powerful validation test of the clusters was conducted using the Classification and Regression Trees

(CART) procedure (Breiman et al., 1984). The CART procedure builds trees by making successive binary splits on predictor variables that explain the most variance in the dependent variable. For this validation test, the dependent variables were the sixteen 1983 and seventeen 1986 clusters that had been produced by the cluster routines. The predictor variables were the same set of variables used to form the clusters. In other words, the test was whether CART, using a very different statistical approach to the problem, would correctly assign the households into the clusters to which the cluster routine said they belonged.

The results were very encouraging. In both years, CART suggested some clusters were too small and obscure. Thus for 1983, the 16 clusters were reduced to 14; for 1986, the 17 clusters were reduced to 14. Within this structure, CART assigned 93% of the households to the correct cluster in both 1983 and 1986. Consequently, based on the financial behavior of subjects, 14 segments were identified for both years.

CART confirmed the marginal relative importance of the variable reporting the size of the mortgage on the primary residence. The relative importance for this variable was 29 while all other variables were in the range from 65 to 100.

Having derived the Stage 1 and Stage 2 clusters, the next step was to describe them. Put another way, do the 14 clusters have face validity? This "profiling" exercise on each cluster was completed with the use of both the normalized means of each cluster and the trees grown by the CART test.

The variable means from the two-stage cluster analysis results are shown in table 1. Stage 1 is comprised of the first eleven clusters of table 1. The last three clusters are the Stage 2, high income, clusters. Each cluster is reported according to the mean values of the financial variables that were the defining basis of the clustering procedure. A more complete description of each cluster appears later in the Findings section of this paper.

Correlates of the Clusters

Once clustering was completed through reliance upon these wealth variables, the next step was to look for income, demographic, behavioral and attitudinal variables that would correlate with financial behavior segment as defined by the clusters. For example, two low-income families having the same net worth might appear in different clusters because they distribute their assets differently over portfolio components. Such differences may be explained by demographic differences, e.g., households at different stages of the life cycle or by differences in attitudes toward, for example, risk. The variables used in this step are listed in table 2 and are discussed below in the findings section. Selection of predictors was based on a priori hypotheses from among the variables available in the data base. Sometimes where the variables were categorical and contained many possible categories, simple correlations and cross tabulations were run in order to reduce the total number of predictors, both continuous and categorical, to a manageable number.

Two statistical techniques were employed to uncover the correlates with cluster membership. In the first analyses CART, described above, was used in a more conventional way. The dependent variable was the categorical cluster numbers. CART was asked to find if socioeconomic-demographic-attitudinal variables, a mixture of continuous and categorical variables, could help to explain cluster membership. That is, CART was used in a multivariate analysis of dependence. A tree growing technique like CART is better suited for analysis of this kind of not-well-behaved data than is a more conventional parametric statistical technique. The second analysis employed logistic regression (SAS, 1989) for validating the CART results. These procedures were used for both years independently.

FINDINGS

Correlates with Cluster Membership

The income, demographic, and attitudinal variables used in attempts to correlate membership in the financial clusters are shown in table 2. Now, we know that demographic variables usually do a poor job at explaining membership in a market segment, but it was hoped that here the attitudinal variables would enrich explanatory power. In addition, it was hoped that the CART tree analysis would increase understanding more than was true of more parametric methods of dependence analysis.

In general, there was an increase in understanding of the members of some clusters, but the correlations between cluster and socioeconomic-demographic-attitudinal variables did not hold for all segments. For example, the explanatory variables in the CART analysis could correctly classify more than half the members of a cluster for only three clusters in each year. The logit results had a slightly lesser rate of correct classification overall and assigned all cases to just three clusters. Overall correct classification rates were in 1983, 50.9 percent for CART and 42.6 percent for logistic regression. 1986 rates were 47.4 percent for CART and 42.6 percent for logistic regression.

Slightly abbreviated CART trees for 1983 and 1986 are shown in figures 2 and 3 respectively. Before describing the clusters that were explained by the dependence analysis, it will be useful to look at the relative importance of the predictors. CART does this by calculating an index of relative importance with the most important predictor having an index of 100. These are shown in table 3.

The relative importance of predictors is quite consistent across the two years. The income variables (1305, 1301) and education of the head of the household (1630) are most important. It should come as no surprise that income is the most important determinant of the structure of household balance sheets. The wage growth slope variables (4559, 4560, 1822, 1823) are interesting. They are from linear regressions of annual earnings run on 3-digit occupation codes with age, gender, and race adjustments. The slopes then yield the expected annual real wage growth rate in two age ranges, under 35 and 36 to 55, for, say, white males in a particular occupation. They thereby reflect the influence of occupation, gender and race on earning capacity. This variable, by itself, may be of interest to sellers of financial services who are looking to develop relationships with "emerging wealth groups" (Marinucci, 1991).

Important loan attributes (5513) was a more important predictor in both years than education of spouse (1730) or stage of life cycle (3116, 1131). This variable is based on answers to the question, ". . . In choosing an automobile loan, which of the credit terms . . . would be most important to you . . .?" The classes are: amount of the loan; dollar amount of finance charges; size of monthly payment; APR of interest; rebate for early payoff; security required; amount of down payment. While the results are not entirely consistent across method and year, it appears that size of the monthly payment and APR are the responses that correlate with segment membership.

The other important attitudinal variables are reasons for saving (children, emergencies, real estate, immediate gratification such as vacations, retirement) and attitudes toward borrowing (good for instant gratification, good economics, depends on how used, depends on loan terms, not prudent economics, costs too much, causes people to get into financial trouble). Wealthier segments had more positive attitudes toward borrowing than did poorer segments.

Thus, while income, occupation, education, and life cycle stage were most important in predicting portfolio segment, three attitudinal variables also were correlated significantly with segment membership.

The logistic regressions validate the CART results. The logistic model makes some unfortunate assumptions about the nature of the data and the relationships. The model assumes each predictor has the same effect on each cluster and that the differences among clusters are reflected only in the intercept term. Relationships on the logit dependent variable are assumed to be linear. Consequently, the procedure produces 13 intercepts with the dependent variable being expressed as a cumulative probability of a case being in a cluster or a cluster greater in number. These probabilities are based on the inverse of the cumulative logistic distribution, so the signs on the regression coefficients shown in table 3 all have the reverse sign to the one hypothesized. For example, education has a positive impact on sophistication of portfolio, but will be reported with a negative sign in the regression output. In order to determine the segment to which the prediction equations assign each case, one needs to difference the predicted values and assign a case to a cluster based on where the cumulative probability increases the most.

The Chi Square tests of overall model fit were significant at the .0001 level. There are several nonparametric, rank correlation, R^2 type measures for these models. The most conservative of these produced fits of .46 and .37.

The relative importance of the predictors, as measured by standardized regression coefficients, are shown in table 3. Most are significant with alpha risk of <.01, the remainder with alpha risk <.07 except where noted in that table. Note that the slopes of wage growth (4559 and 4560) are less important in the regression results and the signs in 1986 are contrary to theoretical expectation. This is because they are treated as continuous variables that have the same effect on each segment, where in CART they can be split so as to have discontinuities with different effects in particular branches. In sum, the logistic regression provides strong evidence that the CART trees are meaningful in describing the characteristics of the segments.

The predictive successes of both methods are shown in table 4. For 1983, CART was useful in explaining membership in only Clusters 1, 13, 12 and 14; for 1986, the CART analysis of the predictors explained membership in Clusters 1, 11 (corresponds to 1983 Cluster 13), 12, and 13 (corresponds to

1983 Cluster 14). The logistic regressions identified only the first three of these in both years.

Segment Descriptions

In this section, each segment is described both in terms of the financial variables used to form the cluster and in terms of their socioeconomic-demographic-attitudinal correlates. There is considerable, but not perfect, correspondence between the 1983 clusters and the 1986 clusters. While there are fourteen clusters in each year, the numbers do not always correspond across years. Since balances in both years are expressed in current dollars, the nominal values in the 1986 clusters are going to be greater just due to inflation. This pattern is clear in the mean values for the total sample as shown in table 1. Note in the table that the weighted sample permits estimation of the proportion of household represented by each cluster in the 1983 population. Differences in these population proportions exist between 1983 and 1986 not only because the transition rates between the two years was not the same for all clusters but also because the dropout rates in the total survey were not the same across all clusters.

1983 CLUSTER 1:

Cluster 1 is a large cluster, 861 households, comprising 30.5 percent of the sample but almost 41 percent of the population. It can be described as a low wealth cluster. The average balance in checking and savings accounts was $927 with very little in other investment categories. The mean home value, for example, was just $20,541. Debt was also low across the spectrum from credit card debt to home mortgage.

Note that the financial portfolio data is richer in asset information than in liability information. Above it was noted that the size of home mortgage was the least useful variable in building the clusters. Interestingly, the use of credit card debt was the most important variable in the formation of the clusters.

In the dependence analysis, CART was successful in correctly identifying 89 percent of its members. It is a low income segment with 73 percent earning less than $19,300 in 1982. Another 14 percent earned $19,300 to $30,000. Most of these 87 percent were under 65 years of age. Another 5 percent were over 65 and earned $7,400 to $19,300 in 1982. This latter group had less than a high school education.

The other variables used by CART to identify this segment concerned attitudes toward saving and borrowing. Low wage slopes were significant for this segment and saving was done to achieve short-run goals rather than for retirement or longer-term investing. Members of this segment largely reported they felt installment buying was a bad idea that should be avoided if possible. A greater than average proportion of this segment reported they were in poor health.

<u>1986 CLUSTER 1:</u>

This cluster, that contained 41 percent of households in the population in 1983 now contains just 32 percent of the

1983 population. It remains a cluster with little wealth and low credit card debt. It is a large cluster of 681 households of which CART correctly classified 97 percent in the cluster validation step. The average balances were: $640 in checking and savings; $884 in IRAs and Keoghs; $105 in money markets and CDs; home value of $22,741 offset by mortgages of just $4,873. There were negligible other assets and just $45 in credit card debt.

As with 1983, CART was most successful in correctly identifying members of this cluster in the dependence analysis. It classified 86 percent correctly. Again, this is a large, low-income segment. All members had 1985 incomes below $41,500, and most had incomes under $18,000. However like this segment in 1983, it would be wrong to conclude that the households in this segment are homogeneous. For example, the retired households in this segment, only about 6 percent of the segment, had incomes of less than $14,000 per year. All other households had heads under 65. These younger households included some single parents who, in the main, had 12 or less years of education. Note in figure 3 that low-income consumers who are in cluster 12 were saving for their children or for retirement while cluster 1 households were saving for homes and more immediate gratification.

<u>1983 CLUSTER 2:</u>

Cluster 2 accounted for 4 percent of the households in the 1983 population. Home value distinguished it from its neighboring clusters. The mean home value was $64,295, offset by a modest average mortgage of $16,944. Average financial assets were of medium size in most categories and were distributed widely among them: $3,185 in checking and savings accounts; $2,911 in IRA and Keogh accounts; $6,297 in money markets and CDs; $3,431 in stocks and mutual funds; business assets were $3,710 (The standard deviation of this variable was three times the mean indicating many zero values and a few small business owners.) Credit card debt was low.

Generally in the dependence analysis, both analytic techniques placed members of segments 2 through 10 in Cluster 1. The socioeconomic-demographic-attitudinal variables did not predict the structures of the portfolios of these segments. It is important to recognize that the borrowing and investing habits of the segments are really quite different from one another, with perhaps the exception of Clusters 6, 9, and 10. It is just that the portfolios cannot be correlated with the predictor variables tested here.

<u>1986 CLUSTER 2:</u>

By 1986, Segment 2 was somewhat more liquid. It was composed of 262 households of which CART correctly classified 90 percent in the validation test. This cluster accounts for 10.6 percent of 1983 households, differentiated by a relatively high home value was $68,186 offset by somewhat higher mortgage levels of $20,654. The other balances were: $4,985 in checking and savings; $2,942 in IRA and Keogh accounts; $3,180 in money markets and CDs; Credit card debt was just $33.

As with 1983, CART could not uncover very much relationship between the portfolios of segments 2 through 10 and the predictor variables. The correctly identified members of Cluster 2 had incomes between $14,000 and $41,500 and believed the amount of the loan was the most important consideration in making a automobile loan.

1983 CLUSTER 3:

Cluster three, containing 8.3 percent of the households in the population, resembles Cluster 1 in most ways except for higher credit card debt, averaging $378. Assets had low average values in all categories: $1,060 in checking and savings accounts; $34 in IRA and Keogh accounts; $694 in money markets and CDs; $171 in bonds. (The standard deviations in these latter two categories were quite large.) Business assets were small, as were home value ($35,675) and home mortgages ($14,240).

1986 CLUSTER 3:

By 1986, this segment has grown in importance, 11.6 percent of the 1983 population, and fell between Clusters 1 and 2 in wealth. The CART validation test classified 90 percent correctly. Average credit card debt had grown to $661. In the dependence analysis, the correctly identified members of this segment had incomes between $14,000 and $49,700 and had two or more children in the nest.

1983 CLUSTER 4:

This cluster, comprising 4 percent of the households differs from Cluster 3 only in that they hold relatively large cash value life insurance, $7,988. Other assets are much like those of Cluster 3: $1,709 in checking and savings; $498 in IRAs and Keoghs; $1,240 in money markets and CDs; $44,998 average home value offset by just $12,321 in mortgages. Credit card debt averaged $204.

1986 CLUSTER 5:

Segment 4 clustered in the 5th cluster in 1986. It was somewhat more affluent than clusters 2 or 4 and was distinguished by high average cash value of life insurance, $10,004. It represented 4.2 percent of 1983 households. CART correctly classified 90 percent of the members of this cluster in validation. Business assets were $1,769, but the standard deviation was five times the mean. Credit card debt remained a low $288. In neither year did membership in this cluster correlate with the predictor variables.

1983 CLUSTER 5:

Clusters 5 through 11 are each small and relatively similar in terms of portfolios. Taken together, they comprised 13.5 percent of the sample and 14.8 percent of the 1983 population of households.

Cluster 5, comprising about 4 percent of households, differs from Cluster 3 and 4 in that there are greater business assets, some stocks and mutual funds in the portfolio and greater credit card debt ($893).

<u>1986 CLUSTER 4:</u>

The corresponding cluster in 1986 resembled cluster 2 except that cash was lower and credit card debt had a large balance of $1,438. This cluster would have comprised 4.7 percent of 1983 households. The members of Cluster 4 correctly identified by CART had incomes between $18,000 and $41,500 and held prudent attitudes toward borrowing.

<u>1983 CLUSTER 6:</u>

Cluster 6, comprising just 1 percent households, is more affluent, entrepreneurial, and independent, but financially conservative and unsophisticated. In the validation test, CART correctly classified only 56 percent of this cluster.

<u>1986 CLUSTER 6:</u>

1986 clusters 6 through 10 were all small, comprising just 7.1 percent of the sample. Cluster 6 is a small, house-rich, cluster of just 65 households, of which CART correctly classified 92 percent. Home value of $92,227 offset by just $8,816 in mortgages. Financial portfolios again were rather conservative and liquid: $5,446 in IRAs and Keoghs; a large $28,893 in money market accounts and CDs; $945 in business assets (again with coefficient of variation of five). Credit card debt was negligible.

1983 CLUSTER 7:

Cluster 7 looks a great deal like Cluster 4 except that cash balances were greater and life insurance smaller. About 3.5 percent of households are in this cluster.

1986 CLUSTER 7:

If Cluster 6 was distinguished by its liquidity in money market accounts, Cluster 7 was distinguished by its liquidity in cash. CART validated 90 percent of 31 households in this cluster. Average balances in checking and savings accounts was $18,400. All other balances were moderate or low.

1983 CLUSTERS 8, 9, 10, 11:

Clusters 8, 9, and 10 probably do not have one-to-one correspondence with their 1986 clusters. Therefore, they will be discussed together. Cluster 8, 75 households comprising 3 percent of the population, resembles Cluster 7 except that liquid assets have been placed in money markets and CDs and home mortgages are lower.

Clusters 9 and 10 are small clusters both in terms of the sample and of the population. Each represents about one percent of the population. Cluster 9 contained only 24 households and CART validated only 75 percent of these. This cluster was a bit of an outlier in that its only distinguishing feature was that it averaged $2,588 in "other financial assets" -- greater than other stage 1 clusters. Cluster 10 had 29 households, and CART validated only 34 percent of these. It is distinguished because it was comprised of households with higher asset levels, particularly bonds, and very few liabilities.

Cluster 11 represents about one percent of the population. It is a small, moderately affluent cluster of just 16 households that is probably distinguished by the highest stage 1 level of other financial assets, $6,165. This cluster has no 1986 counterpart.

<u>1986 CLUSTERS 8, 9, 10:</u>

Cluster 8 in 1986 was smaller than in 1983, just 32 households, of which CART validated 94 percent. This cluster is distinguished by large business assets of $31,417 and negligible assets in CDs, stocks, bonds, or life insurance. Cluster 9 is very like cluster 8 except that average business value and average home values were greater. Home value was about equal to that of cluster 6. In fact, CART misclassified 18 percent of the households in this cluster and placed over half the misclassifications in cluster 8.

Cluster 10 contained only 39 households of which CART could validate just 64 percent. The CART misclassifications were quite evenly distributed into other clusters. The financial assets of this portfolio are well diversified but rather liquid. Average balances were: $7,218 in checking and savings; $9,812 in IRA and Keogh accounts; $6,767 in money market and CD accounts; $9,734 in bonds; $4,718 in stocks and mutual funds. Credit card debt was just $268.

1983 CLUSTER 13:

The final three clusters are from the special oversampled, high-income strata of the sample. Thus, their large numbers in the sample do not reflect their proportion in the population.

Cluster 13 was somewhat less wealthy than Cluster 12 and 14 and had greater debt. It comprised 10 percent of the households in the population. Average consumer debt was $2,221. The average balances of the asset portfolio were: $3,601 in checking and savings; $2,377 in IRAs and Keoghs; $7,013 in money markets and CDs; $5,353 in bonds; $21,565 in stocks and mutual funds; $6,159 in other financial assets; $4,293 in cash value of life insurance; $70,040 in business assets (coefficient of variation equal 7); home value of $77,826 offset by mortgages of $28,786.

In the dependence analysis, CART could correctly classify only 17 percent of the members of this cluster. 94 percent of the households in this cluster had incomes between $42,700 and $56,500, so the income range for this group was narrower than for the other clusters. Members of this cluster had university education but had wage slopes that were somewhat lower than the other high-income segments. The correctly classified members of this segment had not retired and were saving for the future.

1986 CLUSTER 11:

The corresponding 1986 segment was the 11th cluster. It contained 303 households that represented about 11 percent of both the sample and the population of 1983. CART validated 95 percent of these households. This cluster, like cluster 10, was quite diversified, but the balances in each category were greater. Its distinguishing feature was the high level of credit card debt, $3,926. The asset balances were: $4,511 in checking and saving; $5,034 in IRA and Keogh accounts; $4,211 in money markets and CDs; $1,651 in bonds; $4,106 in stocks; $3,241 in other financial assets; $5,180 in cash value of life insurance; $41,900 in business assets (coefficient of variation of 6); home value $79,655 offset by mortgages of $26,818.

In the dependence analysis, CART could correctly classify 37 percent of the members of this cluster. As in 1983, this segment was composed largely of university educated people. While the income range is wide, $18,000 to $50,000 per year, the concentration is in the $40,000 range, similar to the corresponding segment in 1983. This cluster has a positive attitude toward borrowing for rather short-run objectives as long as the monthly payments were within reasonable bounds. In 1983, this group was identified as saving for the future.

1983 CLUSTER 12:

Cluster 12 was the largest of the high wealth segments and an important segment of the population in both years. It was comprised of 741 households that accounts for 26.3 percent of the sample and 17.5 percent of the households in the population. Its wealth and diversified portfolio stand in contrast with that of the previous clusters. The cash value of life insurance, as with Segment 13, was somewhat lower than the balances of other assets. The average balances were: \$15,225 in checking and saving accounts; \$14,113 in IRA and Keogh accounts; \$45,735 in CDs; \$49,558 in bonds (large standard deviation); \$159,246 in stocks and mutual funds (coefficient of variation equal three); \$13,475 in cash value of life insurance; \$222,326 in business assets; \$134,300 in home value offset by a mortgage of \$23,564. Credit card debt was negligible.

The dependence analysis showed this to be largely a high-income segment with 57 percent having had incomes between \$56,500 and \$696,000. CART correctly classified 72 percent of the members of this cluster. In most other respects, it is a very diverse cluster. For example: 16 percent of this cluster were retired, college educated households with incomes in the \$7,440 to \$56,500 range; another 25 percent were younger households with incomes in the \$26,600 to \$56,500 range who were saving for retirement, their own or their children's education, emergencies, or a home purchase. This latter 25 percent believed it may be appropriate to make an installment purchases for a big-ticket durable product in some situations. In making such a purchase they believed the size of the monthly payment and the interest rate are the most important characteristics of the loan to consider. Most members of this segment had been in occupations with high wage slopes during the under age 35 years.

<u>1986 CLUSTERS 12 AND 14:</u>

In 1986, cluster 12 contained 745 households making up 26.4% of the sample and representing 18.4% of the households in the 1983 population. It was the second largest of the clusters. CART validated 92 percent of these. Business assets for this cluster averaged $253,313. Credit card debt was negligible and other assets balances were relatively large. There were average balances of $22,765 in checking and savings; $33,312 in IRAs and Keoghs; $85,241 in money markets and CDs; $73,136 in bonds; $179,000 in stocks and mutual funds; $74,047 in other financial assets; $17,520 in cash value of life insurance; value of home was $166,365 offset by a relatively small mortgage of $25,524.

In the dependence analysis, about 43 percent of this cluster were identified only by the fact that they had incomes between $87,900 and $596,000 -- again similar to 1983. Another 28 percent of the cluster were retired and reported incomes of less than $87,900. Of the working heads of household, they were in occupations with high wage growth slopes under age 35. In all these respects and also with regard to borrowing and saving attitudes, these findings are very similar to those reported for Cluster 12 in 1983. CART correctly classified 72 percent of this cluster.

Cluster 14 combined with Cluster 12 in the 1986 analysis. Neither CART nor the logistic regressions could find correlates with membership in this cluster. It must be classified as a transitory cluster or a statistical artifact. In terms of the financial variables, this cluster was similar to Cluster 12 in wealth but was distinguished from it in that assets are more liquid and portfolios not quite as balanced. There are 28 households in this cluster representing just 0.2 percent of the population. CART validated 96 percent of them. The balances were $415,869 in checking and savings; $70,842 in IRAs and Keoghs; $361,656 in money markets and CDs; $306,071 in bonds; $1,324,187 in stocks and mutual funds; $237,334 in other financial assets; just $24,756 in life insurance; $1,573,473 in business assets; $389,071 in home value with an average mortgage of $27,862; negligible credit card debt.

Thus, clusters 12 in 1983 and 12 and 14 in 1986 are homogeneous with regard to portfolio, but quite diverse with regard to the predictor characteristics. It is important to observe that, as is the case with most segments, age or life cycle, alone, would not have been an efficient segmentation variable.

<u>1983 CLUSTER 14:</u>

This cluster is the wealthiest in the sample. It is based on just 92 households that comprised only 0.2 percent of all households in 1983. The CART validation test classified just 79 percent of these correctly, most often misclassifying members of this cluster as belonging to Cluster 12.

The average balances of the asset portfolio were quite high. This cluster had negligible consumer debt. The portfolio was composed of: $78,400 in checking and saving accounts; $89,612 in IRA and Keogh accounts; $408,041 in money markets and CDs; $900,904 in bonds; $3,448,768 in stocks and mutual funds; $1,405,762 in other financial assets; $73,610 in cash value of life insurance; $751,636 in home value offset by mortgages of $64,237; and a very large $5,259,749 in business assets.

This is the cluster that had the greatest income, over $395,000 per year. Indeed, 25 percent reported incomes over $696,000 per year. CART correctly identified just 60 percent of the members of this cluster. One distinguishing characteristic of this group, as contrasted with cluster 13, is that respondents reported saving for emergencies and for immediate gratification rather than investing for the future. Presumably, they had already made provisions for their future security.

1986 CLUSTER 13:

The corresponding segment in 1986 was cluster 13. Again, this was the wealthiest cluster in the sample. There were just 81 households in this cluster representing just 0.1 percent of households. CART misclassified some of these households as cluster 12. Both had balanced portfolios. Cluster 13 just had greater balances. The averages were $88,362 in checking and savings; $192,392 in IRA and Keogh accounts; $635,882 in money markets and CDs; $1,149,086 in bonds; $4,598,581 in stocks and mutual funds; $2,123,069 in other financial assets; just $42,617 in cash value of life insurance; $5,267,799 in business assets; $893,182 in home value offset by $129,417 in a mortgage. Credit card debt was just $780.

This was an easy cluster for CART to describe. Its members all had incomes in 1985 over $596,000. CART correctly identified 54 percent of this cluster based on this criterion alone. In addition, the members of this cluster were well educated. Again, the findings here are very similar to those for 1983 Cluster 14.

Notice that in both years, there were six clusters (6 through 11 in 1983; 6 through 10 plus 14 in 1986) that were absolutely small and that did not correlate with the predictor variables. These clusters comprised just 11 percent and 7 percent, respectively, of the populations in the two years.

Of the remaining eight clusters, four appear to be real behavioral segments (2, 3, 4 [1986 Cluster 5], and 5) without socioeconomic-demographic-attitudinal correlates. These comprised 20 percent and 31 percent of the population in the two years. Four (1, 12, 13 [1986 Cluster 11], and 14 [1986 Cluster 13]) are behavioral segments that do have socio-economic-demographic-attitudinal correlates. These four, about which the most can be said, comprise 69 percent and 62 percent of the population in the two years.

All eight of the clusters in the last two groups are relatively stable in their characteristics between years. Combining the financial and personal information for the households in these samples provides a solid basis for segmentation. However, it is also important to note that stage of life cycle was only the fifth or sixth most important predictor, after income, wage growth, and education. These findings are consistent with those of Burnett and Wilkes (1985, p. 63) who found that age alone was not an adequate segmentation variable. "Particular bank-related behaviors may be found in any of the age groups. Further, when considered with the covariates of education and income, income turns out to be more important."

Before developing managerial implications of these findings in more detail, it is useful to investigate the extent to which households remained in the same segment or migrated to a new segment between 1983 and 1986.

<u>Cluster Switching Behavior, 1983 to 1986</u>

The cluster switching matrix relating 1983 clusters and 1986 clusters is shown in table 5. This table helps in understanding segment stability and the rate at which 1983 cluster members transition to other clusters. Of course, what appears to be a switch in segment may, in fact, simply reflect a misclassification of segment in the cluster analysis. This possibility is most probable in those segments where membership could not be validated by the CART analysis of the financial variables.

In this discussion, segments will be identified by their 1983 cluster number. 1983 clusters 4 and 5 switched numbers in 1986; 1983 clusters 6 through 11 are 6 through 10 in 1986; 1983 cluster 13 becomes cluster 11 in 1986; 1983 cluster 12 broke into clusters 12 and 14 in 1986; 1983 cluster 14 is 1986 cluster 13. The least switching occurred in segments 1, 4, 12, and 14 where over half the households remained in their 1983 cluster.

Some members of segment 1 switched to segments 2 and 3 by 1986. The latter reflect an increase in value of home or increased use of credit card debt. Still, the low wealth segment remained largely a low wealth segment.

Those members of segment 2, a low wealth segment except for home equity, that switched went most frequently to segments 1, 3, 6, and 12. Segments 6 and 12 are both entrepreneurial, suggesting that some members of segment 2 were small business owners. The 18 percent of these that moved to segment 12 were quite successful in these independent businesses.

Segment 3 is similar to segments 1 and 2 except for greater credit card use. Note that there was significant switching between these two segments over the two years. T tests were performed on the key characteristics of stayers and switchers in this segment. It turns out that those who switched were already significantly different from those who stayed in 1983. The switchers had greater incomes and either head or spouse were over 65 in 1983.

Segment 4, a high life insurance segment, was relatively stable between the two years.

Segment 5 was a more financially savvy segment that invested in a relatively diverse portfolio. By 1986, most of this segment turns up in 1986 segment 11, a somewhat wealthier segment that also had a relatively diverse portfolio. Thus, this segment reflects the way that "financial sophistication" has an influence independent of wealth or age.

Segments 6 through 11 were as blurred in the switching analysis as they were in other respects. There was considerable switching in both directions between segments 6 and 8. Most of 1983 segment 9 turns up in segments 1 and 2 by 1986. Bond holder segment 10 continued to invest heavily in bonds in 1986. Segments 7 and 11 were diffuse.

Some 46 percent of segment 13 remained in that segment while 15 percent moved to segment 12. This segment, the first of the high income stage segments, was characterized in 1983 by a net worth of approximately $161,000 composed chiefly of $22,000 in stocks, $70,000 in business assets and $78,000 in home value. Those members of this segment who remain in 1986 had significantly reduced balances in stocks and business assets, so that net worth was just $119,000. Those who moved to segment 12 had prospered and reported greater balances in all these assets. It is interesting to note that those who switched from 13 to 12 had, already in 1983, significantly greater income that those who did not switch.

Segment 12 was the most stable segment between the two years. It had a diversified portfolio with net worth of $630,000 in 1983 and $879,000 by 1986, a substantial increase. The 1986 cluster 14 portion of this segment is similar but with a very significantly greater net worth of over $4.5 million. Could it be that this 0.2 percent of 1983 households enjoyed a seven-fold increase in net worth in just two years? Without doubt, segment 12 fared very well financially during this three-year period.

Fifty-six percent of wealthy segment 14 stayed in this most wealthy segment in 1986 while 42 percent moved back to segment 12. Of those that stayed, their portfolio composition remained about the same, while their net worth increased by 20 percent in monetary terms to $14.9 million. Those who moved back to segment 12 were already significantly different from those who stayed in 1983. Their incomes averaged $49,000 per year while whose who stayed averaged $81,000. Their wage slopes also indicated lower earning power. Finally, the household heads had slightly less education.

An interesting question regarding switching behavior is whether it was caused by changes in income and demographic factors or whether it was simply a change in the structure of the financial portfolio, perhaps motivated by the changes in the industry that were going on then. To be more precise, there are three hypotheses of interest here.

1. On the characteristics measured in this study, switchers were already different from stayers in 1983.

2. While the switchers and stayers were homogeneous in 1983, they changed differentially on the characteristics measured between the two years.

3. While not different on the characteristics measured, the switchers made significant changes in their financial portfolios between the two years. These shifts in portfolio composition may have been caused by the changes in the industry that were taking place during this period or simply have been personal investment decisions.

4. The factors triggering the change in portfolios were caused by personal characteristics not measured in the study.

In an effort to shed light on that question, switchers and nonswitchers in the larger cells were analyzed with t tests on the means of some key predictor variables. Clusters 2, 3, 5, 13, and 14 were involved in this analysis. Clusters 1, 4, and 12 had switching proportions under 0.5. In no case could hypothesis 2 above be accepted. Stayers and switchers in clusters 2 and 5 were homogeneous with regard to characteristics in both years but had switching rates of .8 -- thus supporting hypotheses 3 and 4. Switchers from cluster 3 were retired and were adjusting their retirement portfolios -- hypothesis 3. Switchers from clusters 13 and 14 into cluster

12 were different in terms of income in 1983 -- hypothesis 1. Those who switched from 13 to 12 had greater incomes in 1983; those who switched from 14 to 12 had lower incomes in 1983.

MANAGERIAL IMPLICATIONS

What constitutes a high switching rate? Just how stable are financial portfolios in normal economic periods? One might expect switching as a result of retirement, as was the case in cluster 3, or significant change in income, that might be suggested by switchers from clusters 13 and 14. However, the only really stable portfolios were those of the stayers in cluster 12 with a switching rate of .26. Next came clusters 1, 4, and 14 with switching rates of .43. Members of cluster 1 have such small portfolios as to have nothing to switch. Switching in the other clusters is quite high; clusters 2 and 5 are the most volatile. These findings suggest opportunities for sellers of financial services and suggest directions for the development of a particular seller's marketing plan aimed at each segment -- or at least each of the more important segments. It is important to remember that these are <u>product</u> market segments, not <u>brand</u> market segments. That is, strategies are suggested for how to market and cross-sell particular financial products to each segment. Recommendations for the positioning of a particular seller in this marketplace are not provided. The marketing implications will now be suggested by segment.

Segment 1, while least interesting from an assets to invest point of view, comprises at least a third of the population. It therefore cannot be neglected. However, the marketing approach is likely to be one of mass, relatively inexpensive marketing promoting basic savings products. The socioeconomic-demographic-attitudinal descriptors of this segment are specific enough to help in focusing promotional campaigns.

While low income, segment 2 offers opportunities for sellers of real estate secured products. Home equity loans or reverse mortgages might be products to target to this segment.

Segment 3 is more important. It contains over 10 percent of the population. While the incomes in this segment are somewhat greater than in segment 1, its distinguishing feature is willingness to use credit card debt. Thus, sellers of credit card products may have an interest in this segment. In addition, retirees in this segment appear prepared to respond to new investment opportunities.

Segment 4 contained something over 4 percent of the population in 1983. Its members had purchased whole life insurance in the past. Perhaps its members are receptive to purchase of more life insurance products. Unfortunately, correlations with the nonfinancial predictor variables were weak for this segment. Life insurance sellers may find modern micromarketing techniques useful in selling existing customers in this segment. On the other hand, it could be reasoned that this segment has all the life insurance they need, and instead segments in a similar financial situation (segments 2, 3, 5) should be targeted for life insurance. For the sellers of life insurance, segment 4 should offer presently untapped opportunities for cross-selling based on the personal relationships already established.

Segments 5 though 11, which taken together comprise about 13 percent of the population, require a different approach. It is important to see that in terms of their financial portfolios, these segments are really different and have high switching rates. For example, segment 6 were heavy buyers of money market and CD investments. Unfortunately, membership in these segments is difficult to identify with available demographic predictors. Therefore, they are candidates for micromarketing approaches. Direct mail should be used to attempt to refine and enrich a data base of households that respond favorably to particular kinds of financial products. It is exactly these behavioral segments for which micromarketing is efficient and effective.

Segment 13 (1986 segment 11) comprised over 10 percent of the 1983 population but had incomes in the $40,000 range, below those of segment 12. This segment is important because they are younger households who are projected to have relative high earning power and more assets to invest at later stages of their life cycle. It is a useful segment to develop. If a financial institution is not concerned with geographical mobility (say a major brokerage house) then it may be desirable to try to identify such people by promoting loan products to them and to begin a data base for future direct, micromarketing over several decades. For institutions such as banks with restricted geographic coverage, micromarketing may not be cost effective.

Segment 12 is an important segment because it comprises about 18 percent of the population and because it has financial resources and annual incomes over $85,000 in 1986. However, it has a broad age distribution made up of both retired and working heads of household. Thus, one might begin to identify and attract members of this segment with mass marketing techniques. However, building a data base of responders to impersonal marketing approaches should pay off in the end. After all, this is a more sophisticated segment. At some point, they are going to expect personal attention from sellers. Management of the relationship is the key to success here, again suggesting a personalized micromarketing approach.

Segment 14 (1986 segment 13) is very small, comprising about one quarter of one percent of the 1983 population. While annual incomes of this segment were over $400,000 in 1983 (over $500,000 in 1986) and net worth averaged just under $15 million, this is a fairly diverse group. Probably, there is considerable inherited wealth in this segment. Thus, these households have established financial services relationships and any changes in these established relationships, are going to require strong personal selling efforts. Only selected financial institutions have the capability to pursue this segment.

In sum, this analysis provides guidelines for estimating the relative effectiveness and efficiency of mass marketing, direct marketing, and micromarketing. Insights have been made possible because of the identification of balance sheet characteristics and their correlation, or lack of correlation, with socioeconomic-demographic-attitudinal predictors. For all clusters there are implications for cross-selling based on both financial and personal characteristics.

SUMMARY

This paper has been able to make a contribution to the segmentation literature for the marketing of financial services because of several strengths. First, the large, probability, national sample of the Survey of Consumer Finances provides a strong base of information useful for managerial application. These Surveys were particularly useful because of the inclusion of attitudinal variables and their oversampling of high income households. Second, the longitudinal design of reinterviewing the same households in 1986 provided panel data on a very large scale that helps our insights into the response of consumers to the rapid changes in the delivery system for financial services that were taking place at that time. Third, the CART tree analysis permitted a more powerful and insightful analysis of the socioeconomic-demographic-attitudinal correlates with the fourteen financial portfolio clusters than has been possible with more traditional statistical techniques. Fourth, while in no way refuting the hypothesis that there is an age-related priority pattern for acquiring financial assets, the research found more complex relationships suggesting that age, alone, may not be an efficient segmentation variable. Finally, the analysis provides insights for strategies of financial services marketing that give suggestions for an appropriate mix of mass marketing, direct marketing, and micromarketing approaches.

REFERENCES

Avery, Robert B. and Gregory E. Elliehausen (1986), 1983 Survey of Consumer Finances, Washington, DC: Board of Governors of the Federal Reserve System.

_____, _____, Glenn B. Canner and Thomas A. Gustafson (1984A), "1983 Survey of Consumer Finances," Federal Reserve Bulletin, 70 (September), 679-92.

_____, _____, _____, _____, (1984B), "1983 Survey of Consumer Finances: A Second Report," Federal Reserve Bulletin, 70 (December), 857-68.

_____, _____, and Arthur B. Kennickell (1987), "Changes in Consumer Installment Debt: Evidence from the 1983 and 1986 Surveys of Consumer Finances," Federal Reserve Bulletin, 73 (October), 761-78.

Berry, Leonard J. (1979), "Service Strategies in the 1980s," Journal of Retail Banking, 1 (September), 1-10.

Breiman, Leo, Jerome H. Friedman, Richard A. Olshen, and Charles J. Stone (1984), Classification and Regression Trees, Monterey CA: Wadsworth, Inc.

Burnett, John J. and Robert E. Wilkes (1985), "An Appraisal of the Senior Citizen Market Segment," Journal of Retail Banking, 7 (Winter), 57-64.

Dickinson, John R. and Eric Kirzner (1986), "Priority Patterns of Acquisition of Financial Assets," Journal of the Academy of Marketing Science, 14 (Summer), 43-49.

Elrod, Terry and Russell S. Winer (1982), An Empirical Evaluation of Aggregation Approaches for Developing Market Segments," Journal of Marketing, 46 (Fall), 65-74.

Kamakura, Wagner A., Sridhar N. Ramaswami, and Rajendra K. Srivastava (1991), "Applying Latent Trait Analysis in the Evaluation of Prospects For Cross-Selling of Financial Services," International Journal of Research in Marketing, 8 (November), 329-49.

Kinnaird, Donald, Kathleen Shaughnessy, Kenneth D. Struman, and William R. Swinyard (1984), "Market Segmentation of Retail Bank Services: A Model For Management," Journal of Retail Banking, 6 (Fall), 52-63.

Mahajan, Vijay and Arun K. Jain (1978), "An Approach to Normative Segmentation," Journal of Marketing Research, 15 (August), 338-45.

Marinucci, Carla (1991), "Chase Targets Bay of Plenty," San Francisco Examiner, (October 7), B1.

SAS Institute Inc. (1989), SAS/STAT Users' Guide, Vol 2, CARY NC: SAS Institute.

Stafford, Edward F. Jr., Jack J. Kasulis and Robert F. Lusch (1982), "Consumer Behavior in Accumulating Household Financial Assets," Journal of Business Research, 10, 397-417.

Tollefson, John O. and V. Parker Lessig (1978), "Aggregation Criteria in Normative Market Segmentation Theory," Journal of Marketing Research, 15 (August), 346-55.

Yaegel, Thomas (1987), "Using Life Cycle Segmentation to Build an Effective Sales System," Journal of Retail Banking, 9 (Fall), 53-62.

Table A1
Sample Attrition

	Weighted percent of 1983 sample	Percent of 1983 group in 1986	Weighted percent of 1986 sample[i]
Age (head)			
under 25	8.0	56.6	8.6
25 to 34	22.6	62.8	23.7
35 to 44	19.5	68.9	20.8
45 to 54	15.5	67.7	14.4
55 to 64	15.0	69.3	14.5
65 or more	19.4	56.6	18.0
Marital Status			
married	60.6	67.8	64.3
sep/divorced male	4.9	56.9	4.4
sep/divorced female	10.7	66.5	11.2
widowed male	1.9	46.2	1.3
widowed female	9.5	58.0	8.1
never married male	6.3	57.4	5.7
never married female	6.1	49.4	5.0
Race			
Caucasian	82.3	67.5	82.3
Nonwhite or Hispanic	17.7	47.7	17.7
Family Income (1982)			
less than $10,000	24.0	46.5	21.2
$10,000 to $19,999	26.8	62.1	28.7
$20,000 to $29,999	19.3	69.8	19.7
$30,000 to $49,999	19.7	75.2	20.1
$50,000 to $99,999	8.2	77.0	8.3
$100,000 or more	2.0	80.0	2.1
Family Net Worth			
less than $100,000	76.6	61.2	77.4
$100,000 to $249,999	14.7	72.0	13.5
$250,000 to $999,999	7.1	75.0	7.7
$1,000,000 to $2,499,999	1.2	77.2	1.1
$2,500,000 or more	0.5	71.4	0.4

Homeownership			
homeowners	63.4	70.9	64.4
other	36.6	52.1	35.6
Education of the head			
0 to 8 grades	14.5	55.1	14.2
9 to 12 grades	44.9	61.6	45.6
some college	17.7	66.4	17.4
college graduate	22.9	72.7	22.8
Labor force participation			
Married			
only head working	19.0	70.6	20.6
only spouse working	4.0	56.9	3.9
head & spouse working	27.8	73.1	31.1
neither working	9.8	52.0	8.7
Single			
working	22.4	65.1	21.5
not working	17.0	49.1	14.2
Sample			
area-probability	98.2	63.7	98.1
high-income	1.8	82.9	1.9
Total	100.0	64.0	100.0

[i] Groups are defined by their 1983 status.

For the 1986 weight, there are two qualifications to these post-stratification schemes. First, the 1983 SCF interviewed only independent households. However, because at any given time a significant proportion of younger adults are in school or the military, or live with their parents, those younger people living independently at the time of the 1983 SCF are unlikely to represent the population of households of their cohort three years later. Therefore, the sample has not been weighted to represent the population of households with heads aged 24 and under in 1986. Households that fell into that group in 1986 were assigned weights adjusted for attrition

TABLE 1. CLUSTER MEANS OF FINANCIAL VARIABLES
(THOUSANDS OF DOLLARS)

	STAGE 1											STAGE 2			
VARIABLE	1	2	3	4	5	6	7	8	9	10	11	12	13	14	TOTAL
	1983 CLUSTERS														
1406	0.927	3.185	1.060	1.709	1.228	2.336	9.014	3.449	1.369	4.505	2.825	15.225	3.601	78.400	8.047
1408	0.017	2.911	0.034	0.498	0.157	0.530	0.314	0.238	0.396	1.246	0.516	14.113	2.377	89.612	7.060
1410	0.590	6.297	0.694	1.240	0.549	4.416	1.915	22.977	1.667	11.232	8.329	45.735	7.013	408.041	27.497
1404	0.101	0.192	0.068	0.232	0.089	0.091	0.238	0.101	0.204	8.093	1.149	49.598	5.353	900.904	43.115
1402	0.109	3.431	0.171	0.333	0.379	0.781	0.553	0.362	0.557	4.591	1.334	159.246	21.565	3448.768	156.808
1414	0.326	0.534	0.270	7.988	0.646	1.669	1.212	1.025	0.670	0.883	1.310	13.475	4.273	73.610	6.995
1416	0.004	0.022	0.010	0.003	0.018	0.056	0.023	0.053	2.588	0.010	6.165	66.935	6.159	1405.762	64.115
1420	1.121	3.710	0.524	1.112	2.194	98.348	2.319	1.169	0.527	5.672	3.315	222.326	70.040	5259.749	239.291
1513	20.541	64.295	35.675	44.998	40.070	70.094	49.423	47.942	31.873	50.983	60.188	134.300	77.826	751.636	87.818
1428	0.013	0.113	0.378	0.204	0.893	0.097	0.139	0.046	0.219	0.065	0.202	0.086	2.221	0.136	0.350
1526	4.644	16.944	14.240	12.322	14.759	9.664	11.412	4.522	13.334	3.996	9.671	23.564	28.786	64.238	16.398
N	861	103	233	117	99	36	100	75	24	29	16	741	296	92	2822
% SAMPLE	30.5%	3.6%	8.3%	4.1%	3.5%	1.3%	3.5%	2.7%	0.9%	1.0%	0.6%	26.3%	10.5%	3.3%	100.0%
% POP.	40.8%	3.9%	8.3%	4.3%	4.0%	1.0%	3.7%	3.0%	1.0%	1.1%	1.0%	17.5%	10.0%	0.2%	100.0%
1986 CLUSTERS															
1405	0.640	4.985	2.406	3.963	4.062	5.051	18.400	4.358	3.803	7.218	4.511	22.765	88.362	415.869	14.871
1407	0.885	2.942	1.592	2.369	4.451	5.446	4.532	2.990	3.981	9.812	5.034	33.312	192.392	70.842	16.888
1409	0.105	3.181	1.486	2.046	3.416	28.893	1.290	0.272	4.777	6.767	4.211	85.241	635.882	361.656	46.330
1403	0.030	0.399	0.135	0.174	0.157	0.175	0.155	0.007	0.047	9.734	1.651	73.136	1149.086	306.071	55.717
1401	0.082	1.050	0.629	0.674	0.955	1.458	0.635	0.144	1.258	4.718	4.106	179.000	4598.581	1324.187	193.200
1413	0.352	0.575	0.870	0.863	10.004	0.430	0.606	0.725	1.563	2.235	5.180	17.520	42.617	24.756	0.575
1415	0.000	0.000	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.241	74.047	2123.069	237.334	0.575
1419	0.108	0.460	0.152	0.506	1.769	0.945	0.000	31.417	69.319	1.286	41.900	253.313	5267.799	1573.473	240.366
1512	22.741	68.186	45.825	66.270	62.512	92.227	47.597	67.919	92.675	77.244	79.655	166.365	893.182	389.071	109.457
1427	0.045	0.033	0.661	1.438	0.288	0.069	0.118	0.224	0.392	0.268	3.926	0.219	0.780	0.137	0.672
1525	4.873	20.654	16.021	31.608	14.374	8.816	13.787	18.173	21.871	17.263	26.818	25.525	129.417	27.862	21.353
N	681	262	276	127	119	65	31	32	33	39	303	745	81	28	2822
% SAMPLE	24.1%	9.3%	9.8%	4.5%	4.2%	2.3%	1.1%	1.1%	1.2%	1.4%	10.7%	26.4%	2.9%	1.0%	100.0%
% 83 POP.	32.1%	10.6%	11.6%	4.7%	4.2%	2.6%	1.2%	1.1%	0.9%	1.4%	10.9%	18.4%	0.1%	0.2%	100.0%

TABLE 2. VARIABALES USED IN CART AND LOGISTIC REGRESSIONS

VARIABLE NO. 1983	VARIABLE NO. 1986	VARIABLE NAME	VARIABLE TYPE
1305	1301	Income	Interval
·4559	1822	Wage growth slope, Under 35	Interval
4560	1823	Wage growth slope, 36-55	Interval
1630	1630	Education of head	Interval
1730	1730	Education of spouse	Interval
3116	1131	Stage of life cycle	7 Classes
3104	1104	Number in household under 18	Interval
1634	1634	Condition of health, self-report	Interval
5513	5513	Most important attribute of a loan	8 Classes
5502	5502	Attitude toward borrowing	8 Classes
5401	1218	Attitude toward saving, 1st reason	7 Classes
5402	1219	Atitude toward saving, 2d reason	7 Classes

TABLE 3. VARIABLE IMPORTANCE IN CART AND LOGISTIC REGRESSIONS

VARIABLE NAME	83 CART REL IMPORTANCE	86 CART REL IMPORTANCE	LOGIT STD. REGRESSION COEFFICIENTS, 1983	LOGIT STD. REGRESSION COEFFICIENTS, 1986
Income	100	100	-.53	-.42
Wage slope, < 35	52	62	-.11	.06 n
Wage slope, 36-55	48	53	-.09 n	.08 n
Educ. head	59	60	-.30	-.41
Educ. spouse	39	38	-.12	-.26
Life cycle stage	43	42	-.19,-.15,-.13,-.08*	-.16,-.11
Imp. loan attribute	51	46	-.18,-.18,-.18,-.15, -.08,-.06,-.04	-.03 n
1st reason to save	34	34	.11,.11,.10,.09,.06	-.16,-.12,-.06
2d reason to save	36	43	-.09,.05,.04	-.07,-.04
Borrowing attitude	38	45	.04,.03,-.04	-.03
No. in hh. < 18	27	30	-.03 n	-.16
Condition of health	27	29	.06	.10

* With categorical variables, dummy variables were created.

n Indicates alpha risk of >.07.

TABLE 4. CART AND LOGIT ASSIGNMENT ACCURACY

PREDICTED	CART								LOGIT					
CLUSTER	1	2	3	4	5-11	12	13	14	1	2-11	12	13	14	TOTAL
ACTUAL CLUSTER 1983														
1	769	0	4	0	4	68	16	0	713	0	148	0	0	861
2	37	4	1	0	1	53	6	1	40	0	63	0	0	103
3	164	0	13	0	0	37	19	0	154	0	79	0	0	233
4	78	0	2	0	1	35	1	0	70	0	47	0	0	117
5-11	213	2	5	0	12	128	19	0	205	0	174	0	0	379
12	173	0	1	0	1	534	11	21	186	0	484	71	0	741
13	113	0	3	0	3	124	51	2	114	0	176	6	0	296
14	2	0	0	0	0	35	0	55	2	0	23	67	0	92
TOTAL	1549	6	29	0	22	1014	123	79	1484	0	1194	144	0	2822

Correct Assignment = 1436 / 2822 = 50.9% = 1203 / 2822 = 42.6 %

PREDICTED	CART									LOGIT					
CLUSTER	1	2	3	4	5-10	11	12	13	14	1	2-11	12	13	14	TOTAL
ACTUAL CLUSTER 1986															
1	588	8	2	8	0	31	44	0	0	573	0	108	0	0	681
2	112	13	3	6	0	50	78	0	0	123	0	139	0	0	262
3	161	2	10	4	0	60	39	0	0	166	0	110	0	0	276
4	59	0	3	12	0	25	28	0	0	63	0	64	0	0	127
5-10	128	6	2	5	0	62	116	0	0	143	0	176	0	0	319
11	91	0	3	6	0	112	91	0	0	112	0	191	0	0	303
12	129	3	4	11	0	41	535	22	0	153	0	586	6	0	745
13	0	0	0	0	0	0	37	44	0	0	0	64	17	0	81
14	0	0	0	0	0	0	24	4	0	1	0	26	1	0	28
TOTAL	1268	32	27	52	0	381	992	70	0	1334	0	1464	24	0	2822

Correct Assignment = 1338 / 2822 = 47.4 % = 1202 / 2822 = 42.6 %

TABLE 5. CLUSTER SWITCHING MATRIX, 1983 AND 1986 SURVEY OF CONSUMER FINANCES

	1986 Cluster									
	1	2	3	5	4	6-10	11	12,14	13	SUM
1983 Cluster			Frequency							
1	494	114	110	5	26	49	34	29	0	861
2	17	25	15	0	5	20	3	18	0	103
3	70	25	57	0	29	8	38	6	0	233
4	5	1	9	67	2	7	8	18	0	117
5	15	5	17	0	18	3	36	5	0	99
6-11	39	58	22	13	13	56	16	63	0	280
13	23	9	39	9	24	10	135	46	1	296
12	18	25	7	25	10	46	33	549	28	741
14	0	0	0	0	0	1	0	39	52	92
	681	262	276	119	127	200	303	773	81	2822
			Probability							
1	0.574	0.132	0.128	0.006	0.030	0.057	0.039	0.034	0.000	1.000
2	0.165	0.243	0.146	0.000	0.049	0.194	0.029	0.175	0.000	1.000
3	0.300	0.107	0.245	0.000	0.124	0.034	0.163	0.026	0.000	1.000
4	0.043	0.009	0.077	0.573	0.017	0.060	0.068	0.154	0.000	1.000
5	0.152	0.051	0.172	0.000	0.182	0.030	0.364	0.051	0.000	1.000
6-11	0.139	0.207	0.079	0.046	0.046	0.200	0.057	0.225	0.000	1.000
13	0.078	0.030	0.132	0.030	0.081	0.034	0.456	0.155	0.003	1.000
12	0.024	0.034	0.009	0.034	0.013	0.062	0.045	0.741	0.038	1.000
14	0.000	0.000	0.000	0.000	0.000	0.011	0.000	0.424	0.565	1.000

FIGURE 1. HYPOTHESIZED MODEL OF AGGREGATED CLUSTER SEGMENTS AND THEIR DESCRIPTOR CHARACTERISTICS

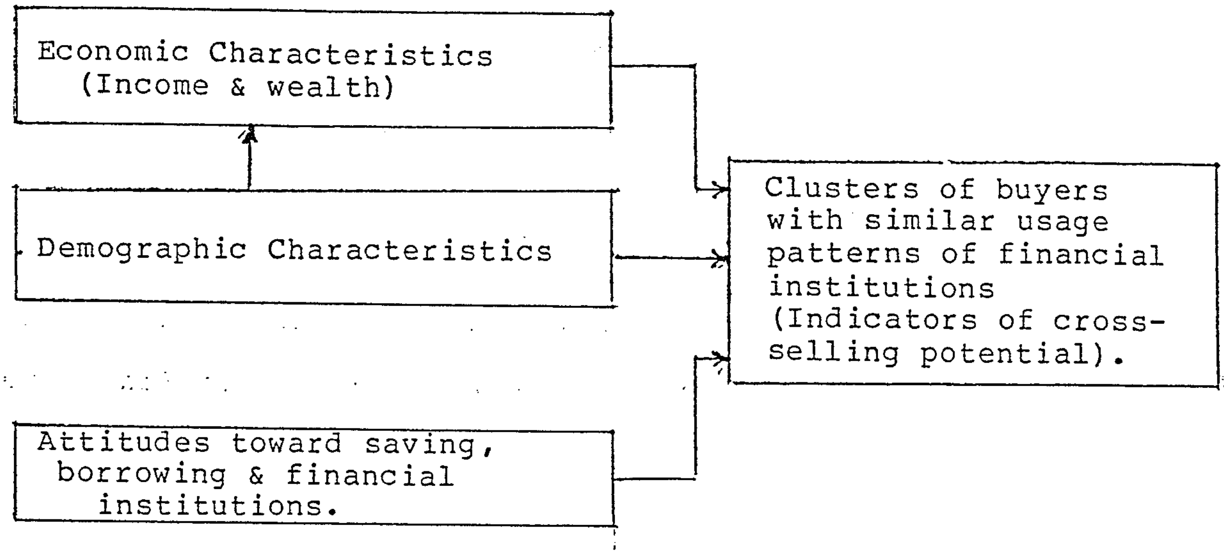
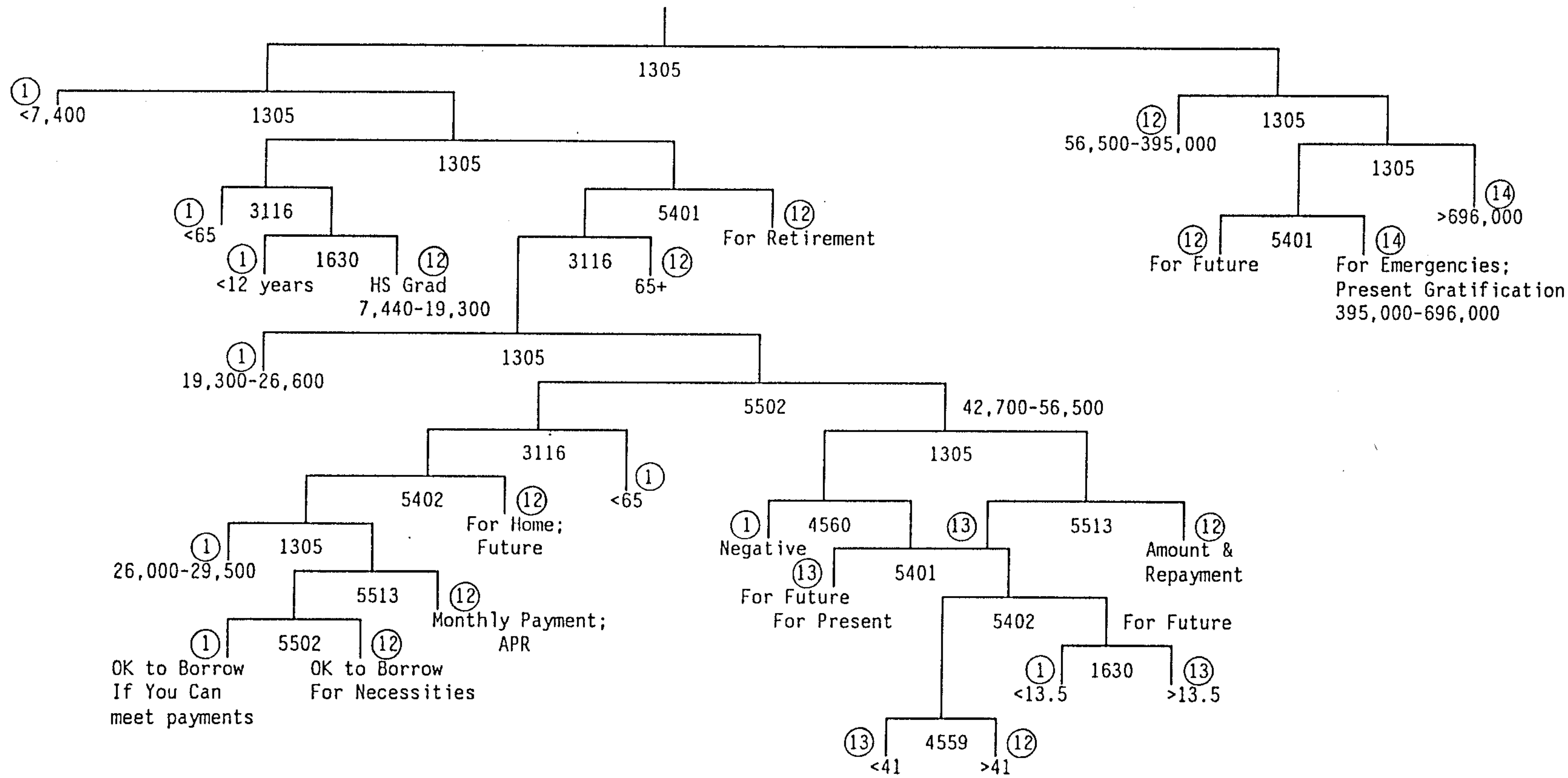


FIGURE 2. 1983 CART TREE

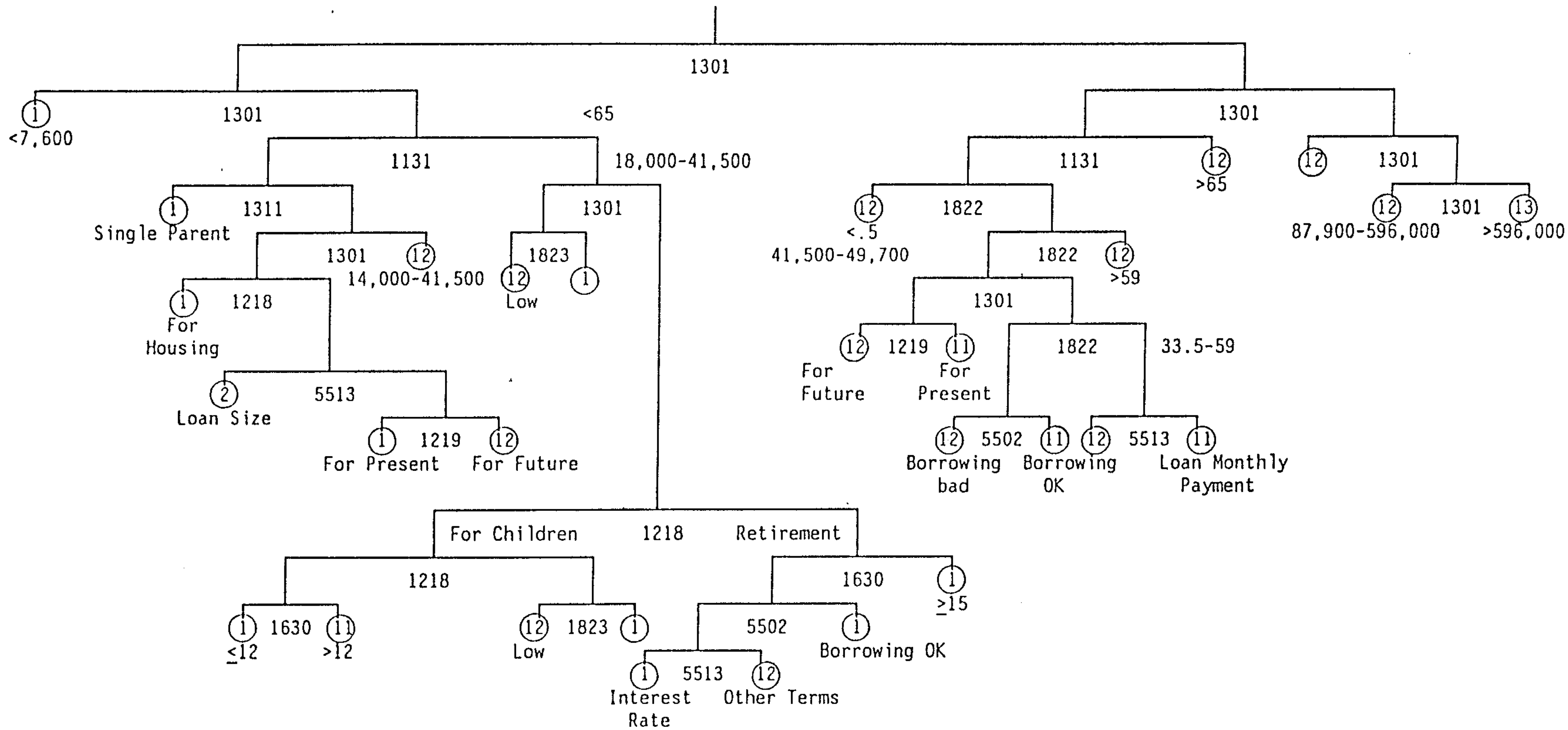


KEY:

Variable definitions shown in Table 2.

Numbers in circles indicate cluster number.

FIGURE 3. 1986 CART TREE



KEY:

Variable definitions shown in Table 2.

Numbers in circles indicate cluster numbers.