Diversification or Concentration?
An Empirical Analysis of Household Portfolio Allocation Practices

Ugis Sprudzs[1]

This article finds that well-diversified portfolios are rare among households owning discretionary financial assets. Most households typically concentrate their portfolios in a single asset class. In 1995, two thirds had average allocations over 90% in constant dollar instruments, while 15% had portfolios dominated by a risky category. After controlling for other variables, differences were found in risk tolerance, shopping behavior, interest rate expectations, and investment goals between groups of households with dissimilar portfolio types. Financial advisors might use this information to develop educational strategies best suited for various portfolio orientations.

Key Words: *Household portfolios, Investment, Saving, Survey of Consumer Finances*

To individual investors as well as professional financial advisors the portfolio allocation process is presented as an integral component of household wealth management. Risk and return vary according to a portfolio's asset class composition, and a household's goal is to select a particular asset blend that meets its return requirements while minimizing risk, where expected return and risk are proxied by past market performance (Kaiser, 1990). Older investors are typically counseled to allocate a greater portfolio share to fixed income and cash, so as to increase liquidity and decrease the risk of capital loss, while young households with long investment horizons are urged to embrace equities. This concept has been packaged into life-cycle mutual funds, which offer different asset mixes for different age groups (Wiegold, 1997). In a similar fashion, the major brokerage firms have *recommended portfolios* which suggest allocation guidelines for their clients and are adjusted from time to time in response to market conditions (McGee, 1998).

For professional financial advisors beginning to use a formal asset allocation program with their clients, it would be helpful to understand the degree to which this process is generally accepted and applied by investing households. To the extent that asset class diversification is not the household's preferred portfolio management tool, advisors will need to educate their clients about the subject before securing their confidence and cooperation. If household investment behaviors deviate from the asset allocation paradigm according to a consistent pattern, advisors can take a generalized educational approach to address the differences between portfolio allocation theory and household practices. On the other hand, if households are heterogeneous in their divergence from the paradigm, a generalized approach may be ineffective. Instead, the advisor's instructional framework may need to recognize the specific characteristics of each household's wealth management style. In this context it would be useful to know if there are groups of households with sufficiently similar investment behaviors so that investor education efforts might be standardized for all members of a group without sacrificing relevance to the individual client.

This article presents evidence from the Federal Reserve's 1995 Survey of Consumer Finances that households can indeed be separated into distinct groups based on the asset allocation patterns found in their discretionary portfolios. Through the use of k-means cluster analysis, nine segments are identified in the data, seven of which are characterized by a high portfolio concentration in a single asset type. Further analysis employing logit regressions suggests that seven of the clusters are also differentiated by a combination of attitudinal or

[1]*Ugis Sprudzs, Senior Consultant with the Financial Services Consulting practice at KPMG Peat Marwick. Address: 411 North Maple Avenue, Oak Park, IL 60302-1809, telephone: 708-386-1823, FAX: 708-386-8316. E-mail: usprudzs@kpmg.com*

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behavioral factors such as risk tolerance, shopping propensity, interest rate expectations, or investment goals, and socio-economic/demographic variables such as financial wealth, age, income, education, sex, and household size. With this knowledge, financial advisors can craft specific educational approaches for the segments they recognize among their current and prospective clients.

The Literature

Previous investigations of household asset allocation practices can be grouped into two broad categories: studies analyzing the parameters of the demand equation for financial assets and studies using a non-assumptive, pattern-seeking methodology. The former are closely linked to the development and validation of economic theory explaining savings versus consumption and the ensuing demand for financial assets. The latter are more oriented toward financial services practitioners and tend to be descriptive rather than theoretical.

Some of the demand equation research has explored the reasons for varying levels of diversification in household portfolios (Uhler & Cragg, 1970; King & Leape, 1987; Ioannides, 1992), where diversification is measured by the number of different asset types owned by the household. Other studies in the group have analyzed the determinants of demand for specific asset categories, where demand is proxied by a binary ownership or non-ownership variable (Uhler & Cragg, Hubbard, 1985; Ioannides, Haliassos & Bertaut, 1995; Xiao, 1996) or a share-of-portfolio measure (Feldstein, 1976; Hubbard, Ioannides, Weagley & Gannon, 1991; Riley & Chow, 1992; Wang & Hanna, 1997; Hochguertel, Alessie & van Soest, 1997). The research on diversification and asset share of portfolio has the greatest relevance for asset allocation issues and will be discussed below.

In one of the earliest examinations of household portfolio diversification, Uhler and Cragg (1970) used 965 observations from the reinterview portions of the 1960, 1961, and 1962 Surveys of Consumer Finance to estimate the effects of net worth, current income, prior period income, age, and family size on the incremental probability of holding an additional asset type. The odds of holding a greater number of assets was found to be positively related to net worth, current income, and income lagged by two periods. A negative association was found with family size. No significant age effect was obtained, a finding later repeated by Blume and Friend (1975) in their analysis of the 1962 Federal Reserve Board Survey.

A different result was reported by King and Leape (1987) in their study of the data from SRI International's 1978 Survey of Consumer Financial Decisions, which contained responses from 6,010 U.S. households, including an oversample of high income households. Their regression model on the number of *information-intensive assets* - defined as stocks, corporate bonds, municipal bonds, savings certificates and savings bonds, Treasury bonds, money market funds and instruments, and single-premium annuities - found the age coefficient to be positive and significant, along with the log of wealth, the marginal tax rate, and two indicators of educational attainment, college and post-graduate education. After noting that portfolio diversification is far from universal even among wealthy households - for example, only 53% of the respondents in the upper 12% of the sample's financial wealth distribution owned equities - they suggested that optimal portfolio construction may be inhibited by lack of exposure to investment information.

Ioannides (1992) expanded on the King and Leape (1987) analysis using 1,622 data points from the 1983 and 1986 waves of the Survey of Consumer Finances. The Ioannides model of the number of household-owned information-intensive assets included two measures of risk tolerance: willingness to make risky investments and willingness to undertake illiquid investments, as well as socio-economic variables denoting marital status, race, health status, absence of borrowing constraints, labor income, and employment status. A separate variable controlled for the household's use of professional investment advice. Ioannides replicated King and Leape's positive age effect, even after controlling for the presence of professional investment advice. The number of information-intensive assets owned was also positively affected by net worth, labor income, employment status, college education, lack of borrowing constraints, and risk tolerance. Other things held constant, more information-intensive assets were owned by married households and those in good health while less were owned by non-white households and those unemployed. Ioannides did not find that the number of information-intensive assets was affected by life events occurring in the previous three years such as a change in jobs, a move by the household, or retirement of the household head or spouse. No gender effect on diversification was observed, and the coefficients on actual or anticipated inheritance were not significant.

Unfortunately, regression models that define diversification as the number of asset categories in a household's portfolio are flawed, since they contain no information on the portfolio's relative exposure to the asset classes represented in it. For example, suppose Household A and Household B both own three asset types: cash, stocks, and bonds, but Household A's portfolio contains these assets in equal proportion while Household B has 70% in cash, 10% in stock, and 20% in bonds. Clearly, diversification is qualitatively different for these two households. The incidence, typology, and correlates of such different asset allocation patterns have not been fully explored, a research gap which this article seeks to fill.

Another strand of the demand equation studies has sought to quantify the factors associated with an individual asset category's share of a household's portfolio. Feldstein's (1976) analysis of personal taxation effects among 1,799 financial asset-owning respondents to the Federal Reserve's 1962 Consumer Finances Study is generally regarded as the pioneering work in this direction. Feldstein estimated six regression equations on the share of portfolio attributable to common stock, preferred stock, taxable bonds, municipal bonds, savings bonds, and bank accounts. After controlling for net worth, age, sex, and the ratio of human capital to non-human net worth, he found that the tax level was positively related to portfolio share invested in common stock and municipal bonds, but negatively affected portfolio share held in bank accounts.

Hubbard (1985) extended Feldstein's (1976) model to include the effect of estimated pension wealth on portfolio composition, predicting that demand for inflation-adjusted or annuity-type assets should decline as the ratio of Social Security benefits to wealth increases. Using data gathered from 4,605 households in 1979 under the auspices of the U.S. President's Commission on Pension Policy, Hubbard estimated share of wealth models for U.S. savings bonds, deposits, bonds, equities, and annuities. The ratio of expected social security benefits to total wealth was found to have a negative coefficient for equities and annuities, as expected, and a positive coefficient for U.S. savings bonds, deposits, and bonds. However, the tax effect was measurably non-zero and positive only for equities.

Ioannides (1992) elaborated a model of portfolio share that allowed for the impact of life events, recent changes in net worth and income, as well as the houshold's earlier allocation to the respective asset class. Aspects of household status and portfolio composition at two points in time were obtained from the 1983 Survey of Consumer Finances and its 1986 follow-up wave with the same sample. In contrast to Feldstein's (1976) results, Ioannides found no significant taxation effect on the share of household net worth invested in stocks, bonds, checking, IRA accounts, and money market funds. Change in household net worth also proved uncorrelated with net worth share in stocks, bonds, and money markets, however the coefficient was negatively significant for checking and IRAs. Change in income did not appear to have a significant impact on any of the financial asset shares while the income level had a negative impact on the share attributable to IRAs. A spouse's retirement had a significantly negative effect on net worth share in stocks and money markets. The value of an asset category's share at the beginning of the time period had a positive and significant effect for share in stocks, checking, and money markets.

The Hubbard (1992) and Ioannides (1976) coefficients are not directly comparable to Feldstein's because they relate to share of wealth or net worth, whereas Feldstein's apply to share of portfolio. In addition, the Hubbard and Ioannides coefficient estimates for net worth share in bonds are unreliable, since they treat tax-exempt and taxable instruments as a single category. However Ioannides' report of the persistence of asset share over time is a theme echoed by other researchers (Skinner, 1992; Papke, Peterson, Mitchell & Poterba, 1993; Thaler, 1994) who have noted that some investment behaviors such as contributions to retirement accounts have very high recurrence rates.

A more generalized type of demand equation analysis focuses on a portfolio's allocation between risky and non-risky assets. This approach was taken. Weagley and Gannon (1991) investigated relative shares of household assets in savings versus housing equity, financial securities, and retirement investments for a group of 249 Missouri households participating in a study of economic well-being in non-metropolitan Missouri. In their article, *financial securities* included all types of stocks, bonds, as well as stock and bond mutual funds. *Savings* were defined as savings accounts, money market deposit accounts, CDs, U.S. Treasury notes and bills, and U.S. savings bonds. Weagley and Gannon observed a significant hump-shaped age effect on the ratio of savings to financial securities, after controlling for wealth: the risky component of household portfolios increased with age, but at a declining rate until a maximum was reached, after which the risky component began to shrink. However, the Weagley and Gannon study may be subject to sample selection bias, since metropolitan areas were not represented in the sample where access to information and transactions costs may be different.

Riley and Chow (1992) analyzed the proportion of household wealth held in *non-risky* assets, defined as personal property, real estate, bonds and checking accounts, using 17,697 observations from Wave IV of the 1984 Survey of Income and Program Participation sponsored by the U.S. Bureau of the Census. They found significant negative coefficients on continuous age, education, wealth, and income variables. They also obtained significantly negative coefficients on dummy variables indicating income over the poverty line and wealth in the upper decile of the wealth distribution. A significant positive coefficient was estimated for a dummy variable representing post-retirement age. Since Riley and Chow's definition of *non-risky* assets included real estate and personal property their findings are not strictly comparable to those of Weagley and Gannon (1991). However, Riley and Chow's age effect is similar to Weagley and Gannon's.

Hochguertel et al. (1997) estimated the share of financial wealth held in risky assets, defined as stocks and bonds, by a sample of 3,077 Dutch households surveyed in 1988 by Research International Nederland. Consistent with Feldstein's (1976) results, they found the risky portfolio share to be positively related to tax rate, after controlling for financial wealth. They also found a significant positive effect for educational level. However, in contrast to Weagley and Gannon (1991) and Riley and Chow (1992), they saw the opposite of a hump-shaped age effect - one that implied declining relative demand for risky assets until age 43 with increasing demand thereafter.

Wang & Hanna (1997) reported monotonically increasing age effects on the proportion of *net wealth* invested in risky assets – for retired as well as non-retired households past a threshold age. Utilizing the 1983-1989 panel data of the Survey of Consumer Finances, they also found risk tolerance to be positively related to net wealth, marital status of married, education, and white or other race ethnicity. Significant negative coefficients were computed for poor health and a recent change in jobs. However, Wang & Hanna's results are not directly comparable to the above studies since they included the present value of expected lifetime employment and pension income in the net wealth calculation.

From a practitioner's perspective, the demand equation research would be useful if it helped a financial advisor compare an individual client's asset mix to the norm in the general population, given what is known about the client household's income, wealth, tax bracket, age, education, and risk tolerance. Unfortunately, as is apparent from the above overview of such studies, the econometric results do not offer consistent guidance in this matter. In a similar, but more extensive review, Hochguertel et al. (1997) compared the shape of the implied age effect in 53 financial asset ownership or demand equations presented in ten studies. In 14 cases it was monotonically increasing, in eight it was hump-shaped, in four it was monotonically decreasing, and in the remainder it was indistinguishable from zero.

Another problem is that share models exhibit relatively poor fit to the data. Feldstein's (1976) equations have R^2 of .37 for common stock, .33 for bank accounts, but .19, .15, .03, and .02 for taxable bonds, municipal bonds, savings bonds, and preferred stock, respectively. Hubbard (1985) reports R^2 of .28 for equities, .24 for deposits and bonds, .22 for savings bonds, and .20 for annuities. Ioannides (1992) reports R^2 of .133 for stocks, and .085, .078, .052, and .007 for money markets, IRAs, checking, and bonds, respectively. Thus it is difficult for the financial advisor to obtain reliable information on what constitutes prevailing houshold portfolio allocation practices from the demand equation type of analysis.

The studies utilizing pattern-seeking research methodologies provide an alternative information source on household financial behavior, particularly Lease, Llewellen and Schlarbaum (1976), Xiao (1995), Sprudzs (1996), and Gunnarson and Wahlund (1997). Lease et al. investigated the hypothesis that different groups of individual investors concentrate on different groups of assets, thus undermining the free flow of capital and the market's ability to establish "coherent risk-return" relationships for all classes of securities. Their data consisted of 972 responses to a 1972 mail survey sent to a geographically stratified sample of 2,500 of a large retail brokerage firm's customers. Lease et al. proposed that their data was representative of "the mass of American shareholders", though it was not projectable to the population of all investors and clearly not to the population at large. However, their work is an early example of a cluster analysis study and is therefore of interest here.

Lease et al. (1976) employed a hierarchical clustering algorithm to partition their respondents into five socio-economic segments differentiated by a combination of age, sex, marital status, annual family income, occcupation, employer type, educational attainment, and family size. Respondent investment strategies, goals, trading patterns, attitudes, and portfolio composition were then compared across groups. Statistically significant differences were ascertained across groups for average asset share in common stock, government bonds, corporate bonds, and savings accounts, while the differences in allocation to preferred stock and mutual funds were not significant. For example, the highest group-specific average asset share in common stock was 45%, in the segment composed of single, predominantly male business professionals with average age 51 and average income of $21,500. The lowest average asset share in common stock was 23%, found among highly educated married males (40% with advanced degrees) with large households (mean family size 4.8), having average income of $33,400 and on average 45 years old. Lease et al.'s exclusive use of socio-economic variables for segment identification left untested the proposition that households might be grouped according to their portfolio allocations. The present article explores this possibility and demonstrates a much greater heterogeneity of portfolio allocations across segments than those reported by Lease et al.

Xiao (1995) examined the Federal Reserve's 1989 Survey of Consumer Finances data for evidence that ownership of one type of financial asset increases the probability of owning another, after controlling for socio-economic factors such as income, household size, home ownership, credit card ownership, age, race, gender, education, marital status, and employment status. The results showed that in 22 out of 36 asset type pairs owning one financial asset increased the chances of owning the other. In eight cases there was no observable effect, in four instances the effect was negative, and in two the effects were asymmetrical. Thus, owning CDs decreased savings plan utilization, and checking was negatively associated with money market account ownership. Savings account ownership also decreased money market account use as well as the ownership of stocks and IRAs. Xiao's analysis, however, did not address the relative weight of each asset type in the overall portfolio. In addition, some coefficients may have been biased because of the absence of a wealth measure from the control variables.

Sprudzs (1996) studied a series of non-public data sets on investment holdings of *affluent* households, where affluence was defined as exceeding $100,000 in annual income or $500,000 in net worth, excluding principal residence. He reported finding five *personal investing styles* among affluent households, four of which were characterized by a high concentration of the *discretionary investment portfolio* in a single asset class. Discretionary investment portfolio was defined as consisting of stocks, bonds, mutual funds, money market accounts, bank savings and CDs, self-administered retirement accounts, and other investments such as hedge funds, limited partnerships, precious metals, futures, and options. The five portfolio types were: the equity-oriented portfolio with 70% of its aggregate holdings in stocks and stock mutual funds, the savings-oriented portfolio with 73% in bank savings and CDs, the cash-oriented portfolio with 65% in money market accounts, the muni-oriented portfolio with 54% in municipal bonds and municipal bond funds, and the diversified portfolio with an aggregate allocation of 26% to equities, 13% to taxable fixed income, 7% to tax-exempt bonds, 15% to money markets, 13% to savings and CDs, and 27% in other investments. This analysis had several drawbacks, which the present article seeks to correct. Its projectability was limited to the affluent segment of the population, its findings were not replicated in public-domain data, and it lacked a description of the k-means clustering methodology used to obtain the portfolio style groupings. Nonetheless, it provides evidence in support of Lease et al.'s (1976) hypothesis that different groups of investors prefer different types of assets.

Gunnarson and Wahlund (1997) explored a variation of this hypothesis in a study of 503 respondents to a mail survey sent to 1,000 randomly selected Swedish households. They employed k-means cluster analysis to segment observations based on dichotomous variables indicating ownership or non-ownership of 25 investment or savings vehicles and 10 loan products. Their segmentation resulted in six groupings which they called Residual Savers, Contractual Savers, Security Savers, Risk Hedgers, Prudent Investors, and one that included *divergent* strategies. Small sample size, the inclusion of debt variables, and the use of binary ownership variables rather than shares may have inhibited the algorithm from obtaining greater differentiation of respondents by their portfolio composition. However, the level of securities holdings differed substantially across the segments, with a median of zero among Residual Savers and Contractual Savers, a median of 15,754 Swedish kronor among Security Savers, 68,000 kronor among Prudent Investors, 146,831 among Risk Hedgers, and 206,000 among those with divergent strategies. There were also differences in the median holdings in savings and transactions accounts: median liquid holdings for Contractual Savers were 9,517 Swedish kronor, among Residual Savers the median was 12,000, for Security Savers it was 23,000, among Risk Hedgers it was 80,664, among Prudent Investors the median was 210,000, and the Divergent Strategies segment had median liquid holdings of 160,000. Consistent with these findings, the Residual Savers, Contractual Savers, and Prudent Investors had the lowest psychological factor score for risk taking, while Risk Hedgers and the Divergent Strategies segment had the highest risk taking scores.

Gunnarson and Wahlund's (1997) results, while not directly pertinent for the U.S. population because of differences in the market environment and product availability, are suggestive of a pattern in portfolio allocation behavior, whereby some household groups hold large amounts of securities while others own large amounts of cash. The current article will develop a more detailed approach to this question using a methodology similar to Gunnarson and Wahlund's, but applied to recent U.S. household data.

Finally, it should be noted that excellent summary information on the household sector's balance sheet, broken down by various demographic categories and trended over time, has been published by the Federal Reserve's research economists and the Bureau of the Census (Kennickell, Starr-McCluer & Sanden, 1997; Eller, 1994). Additional data on the holdings of the wealthy can be found in the IRS analyses of estate tax filings (Johnson, 1998).

Methodology

The purpose at hand is to determine if household groups exist such that portfolio allocations are qualitatively similar within the groups and substantively different when comparing across groups. To provide a non-subjective and robust answer to this question, the researcher can employ one of several quantitative classification methods, which were originally developed for the natural sciences, and are generically known as *cluster analysis* techniques (Everitt, 1993). These have been broadly characterized as *hierarchical* or *nonhierarchical* in nature (Punj & Stewart, 1983). Hierarchical cluster analysis, frequently used to derive taxonomies of biological specimens, produces a sequence of data partitions with increasing internal homogeneity, which may range in size from containing all observations to containing only one. Nonhierarchical, or iterative partitioning approaches begin with a pre-specified number of clusters and successively rearrange cases between them until a maximum homogeneity is reached. With both methods, the researcher must choose the optimum number of clusters to describe the data - ex post with hierarchical methods, ex ante with nonhierarchical techniques. In practice, this means balancing quantitative considerations such as incremental reduction of within-group variance, against the solution's relevance and usefulness for the subject matter (Gunnarson & Wahlund, 1997).

Punj and Stewart (1993), in their review of the comparative efficacy of different clustering algorithms, concluded that the nonhierarchical k-means method outperformed other techniques, particularly if non-random starting points were specified for the cluster centroids. If the initial centroids for a k-means procedure were assigned on a random basis, then hierarchical techniques offered superior cluster identification. For the current analysis, however, previous research (Sprudzs, 1996) offered hypotheses regarding cluster parameters, and thus the k-means approach was selected as the most appropriate classification tool.

A clustering solution gains credibility if it can be replicated by applying the same technique to a new data set or a hold-out sample of the original data (Everitt, 1993). For example, Sprudzs (1996) reported a similar clustering result from separate affluent market data sets collected in 1987, 1991, 1994, and 1995. In the case of the 1995 Survey of Consumer Finances public use file, stability of a cluster solution can be assessed by conducting the same cluster analysis on each of the five data implicates, which are designed to enable estimation of data variability caused by imputation of missing responses (Kennickell, 1997). While the implicates have been described as five complete data sets (Montalto & Sung, 1996), they are not independent sets of observations, since the same respondent households are represented in each implicate. However, an individual household's response data may differ across implicates because elements originally missing due to the respondent's lack of information or non-cooperation have been filled in with values produced by a stochastic multivariate estimation procedure linked to the respondent's background variables. By applying the clustering algorithm to each implicate, the solution's sensitivity to variations in the data can thus be tested.

The input variables for the k-means clustering procedure are shown in Table 1. They were the percentage shares, multiplied by 100, of seven financial product categories in a household's portfolio of discretionary financial assets, here defined as the sum of balances in transaction accounts, savings accounts, CDs, money market deposit accounts, money market funds, as well as the value of individual stocks, bonds, and mutual funds. The seven input variables satisfy two requirements. First, they sum to 100 and thus contain the totality of the household's discretionary financial portfolio. Second, they represent portfolio shares in mutually exclusive financial product categories having different risk, return, and taxability features. Thus stock mutual funds were grouped together with individual stocks, taxable bond funds with individual taxable bonds, and municipal bond funds with individual municipal bonds.

It should be noted that the 1995 Survey of Consumer Finances did not obtain the percentage breakdown of the respondent family's retirement accounts by asset class, nor did it request a separate tally of investments in foreign or global stock mutual funds. Self-directed retirement accounts such as IRAs, Keoghs or 401(k)s were therefore not included in the base or in the input variables. Investments in foreign corporate stock were grouped together with domestic equity.

Households reporting zero discretionary financial assets were assumed to have zero variance on the input variables, assigned to a pre-designated cluster, and excluded from the subsequent clustering procedure.

Table 1
Example of Cluster Analysis Input Variables for Individual Household

Variable Description	Value (%)
Cash in transaction accounts	10
Savings and CDs	5
Money market accounts (MMDA, MMF, cash in brokerage account)	10
Equities (individual stocks and stock mutual funds)	40
Balanced funds (combination mutual funds)	5
Taxable fixed income (federally taxable bonds and bond funds)	15
Tax-exempt fixed income (municipal bonds and muni bond funds)	5
Total	100

Initially, the k-means cluster analysis was performed on the first implicate of the data, specifying increasing numbers of clusters until an intuitively satisfactory solution of nine clusters was obtained. Expansion to a tenth cluster resulted in two segments with qualitatively similar parameters and was thus rejected. Starting cluster means were set to approximate the average portfolio allocations reported by Sprudzs. Software employed was Statistica for Windows, release 5.1.

A nine cluster solution was then computed for each of the remaining data implicates, retaining the same initial cluster means and order of observations. After validating the consistency of input variable means and standard deviations, within clusters, across the implicates, a measure of cluster stability was taken by calculating the number of cases in Implicate One that appeared in the *same* cluster in each of the other implicates. For example, 455 observations were classified into Cluster One in the first implicate. Of these, 79% were assigned to the analog of that cluster in Implicate Two and the average across all four remaining implicates was 81%. Complete results of this are shown in Table 2 below.

Table 2
Percent of Cases Assigned to *Same* Cluster as in Implicate One

Implicate 1	n	Implicate 2	Implicate 3	Implicate 4	Implicate 5	Aver-age
Cluster 1	455	79%	84%	80%	81%	81%
Cluster 2	386	89%	91%	90%	90%	90%
Cluster 3	741	90%	91%	90%	90%	90%
Cluster 4	291	88%	88%	90%	90%	89%
Cluster 5	167	81%	83%	71%	75%	78%
Cluster 6	458	91%	90%	91%	90%	91%
Cluster 7	63	79%	75%	81%	83%	79%
Cluster 8	274	80%	82%	81%	81%	81%
Cluster 9	1091	97%	97%	97%	98%	97%

Clustering consistency ranged from 71% to 98%, with the greatest consistency associated with the largest segment. Five of nine clusters showed consistency of 89% or more, indicating that a robust solution had been obtained.

Cluster means and standard deviations for all implicates can be requested from the author - since they were virtually identical across implicates a comparison table is not presented here. The cluster parameters discussed in the next section are taken from the Implicate One cluster analysis solution.

A battery of financial, demographic, and psychological variables was then used as the independent variables in logistic regressions to determine which of the factors were significantly associated with each of the clusters. These models were run for all clusters except Cluster 7, which had only 63 cases. Regression results from Implicate One are shown. Similar results from the other implicates can be requested from the author.

Findings and Discussion

Average portfolio shares for the seven financial product categories within each cluster in Implicate One are shown in Table 3 and Figure 1, standard deviations are shown in Table 4. The parameters and percentage breakdown of the sample are computed using the population weights supplied with the Survey of Consumer Finances data file, so as to show each cluster according to its estimated incidence in the 1995 general population.

As seen in Table 3, the majority of households can be viewed as holding a portfolio oriented toward, if not concentrated in a single asset category. The most prevalent such portfolio orientation, found among 32% of households, is cash-based – the households in this segment have, on average, 97% of their discretionary financial assets in transaction accounts. Another 21% of households had an average 82% allocated to savings accounts and CDs, with 10% in cash. 8% of households held a combined average of 91% in cash and savings and 7% had a 75% allocation to money market accounts. Thus, approximately two thirds of American households in 1995 had a portfolio allocation highly skewed toward federally-insured accounts or constant-dollar type investments. In the remaining third of the population, however, there is a tendency to hold high concentrations of risky assets. A segment comprising 6% of households had an average 86% of its portfolio invested in equities. 7% of households had on average 66% invested in taxable bonds, and one percent of the sample held 60% of their discretionary portfolio in balanced or combination funds. Approximately one percent of American households had a portfolio dominated by municipal bonds - with an average 3% in cash, 10% in savings/CDs, 10% in money market accounts, 11% in equities, 7% in taxable fixed income, and 56% in muni bonds and tax-free bond funds. Households with a *well-diversified* portfolio in the conventional sense – half in equities and the remainder spread across all other asset classes - comprised only 6% of the population.

As noted above, respondents reporting zero discretionary assets were assigned to an a priori cluster. On a weighted basis they accounted for 12% of the sample.

These cluster analysis results are consistent with the earlier findings of Sprudzs (1996), except that use of methodology with general population sample has led to the identification of three portfolio types, the Cash-oriented, Cash & savings-oriented, and Taxable bond-oriented, which were not apparent in the affluent market data.

The low occurrence of conventionally diversified portfolios may seem puzzling, given the considerable efforts of the media and financial planning profession to promote the concept. It would be helpful, therefore, to investigate which factors are associated in a statistically significant manner with specific portfolio orientations. For example, it may be that households own cash dominant portfolios because they have low incomes and need to maintain portfolio liquidity to fund everyday expenses. An orientation toward FDIC-insured products may be the result of high risk averseness while an equity orientation may reflect high risk tolerance. Overall financial wealth may also impact a household's portfolio orientation. Wealthier households may be more likely to hold a diversified portfolio because transactions costs can be spread over a larger base.

These questions were addressed by estimating a logistic regression for each of the clusters except Cluster 7, which had an insufficient number of observations. Following the methodology employed by Xiao (1995), the independent variables included seven demographic and socio-economic variables to assess and control for the effects of financial wealth, income, education, household size, age, sex, and retirement status. Table 5 shows eleven behavioral or attitudinal factors whose coefficients were also estimated.

Complete results of the logistic regressions are offered in the Appendix (available at the web address www.afcpe.org/ugisAppendix.htm). Tables 6 and 7 summarize the logistic regression results by listing for each portfolio orientation the statistically significant variables and whether the effects were positive or negative. The regression models were estimated from all observations assigned to a portfolio orientation cluster, ie. households without discretionary financial assets were excluded from the regression. Thus the variable coefficients identify those factors that differentiate the members of each individual cluster from the group of all other discretionary financial asset-owning households. Table 6 shows the results for the demographic and socio-economic variables. Table 7 presents them for the behavioral and attitudinal factors.

From a financial advisor's perspective, both sets of coefficients are relevant, but in different ways. Demographic and socio-economic variables such as wealth, age, income, sex, etc. can be viewed as *givens*, since they are client attributes that the financial advisor usually does not control. Nonetheless, they can have an effect on a household's portfolio orientation. Behavioral and attitudinal factors, on the other hand, can be influenced by the advisor through educational efforts and investment experiences provided to the client.

Figure 1
Average Portfolio Allocation Within Each Cluster

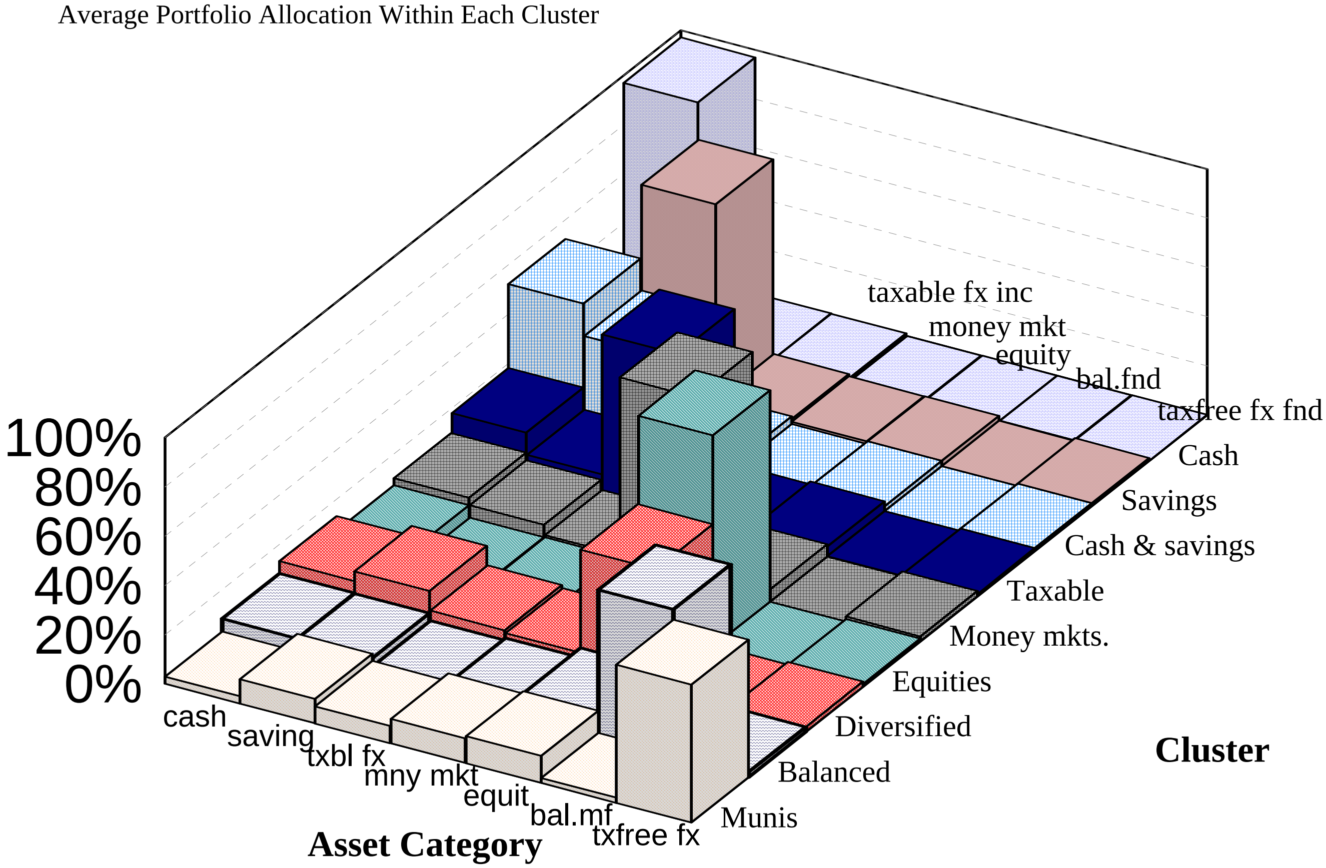

Table 3
Average Portfolio Allocation For Each Cluster

		Average Portfolio Allocation for Each Cluster						
Percent of Sample HH's (weighted)	Cluster Number: Portfolio Orientation	Cash	Savings	Taxable fixed income	Money market	Equities	Balanced funds	Tax-free fixed income
32.0%	9: Cash	**97%**	1%	1%	0%	0%	0%	0%
21.0%	3: Savings	10%	**82%**	3%	2%	2%	0%	1%
8.0%	8: Cash & savings	**52%**	**39%**	4%	1%	2%	0%	1%
6.7%	4: Taxable bonds	18%	9%	**66%**	3%	4%	0%	1%
6.7%	2: Money markets	10%	7%	3%	**75%**	5%	0%	2%
5.8%	6: Equities	7%	2%	2%	2%	**86%**	0%	1%
5.7%	1: Diversified	13%	17%	9%	8%	50%	1%	2%
1.3%	7: Balanced funds	8%	8%	5%	6%	10%	**60%**	2%
.9%	5: Municipal bonds	3%	10%	7%	10%	11%	2%	**56%**
12.0%	No discretionary financial assets	--	--	--	--	--	--	--
100.0%								

Table 4
Standard Deviations of Portfolio Allocations For Each Cluster

		Standard Deviation of Portfolio Allocation in Each Financial Product Category						
Percent of Sample HH's (weighted)	Cluster Number: Portfolio Orientation	Cash	Savings	Taxable fixed income	Money markets	Equities	Balanced funds	Tax-free fixed income
32.0%	9: Cash	**8%**	4%	5%	2%	3%	0%	1%
21.0%	3: Savings	10%	**14%**	8%	8%	6%	2%	3%
8.0%	8: Cash & savings	**14%**	**15%**	9%	7%	6%	1%	4%
6.7%	4: Taxable bonds	18%	13%	**19%**	8%	9%	2%	3%
6.7%	2: Money markets	13%	12%	8%	**19%**	9%	1%	2%
5.8%	6: Equities	8%	4%	5%	5%	**10%**	3%	3%
5.7%	1: Diversified	15%	17%	13%	14%	12%	5%	6%
1.3%	7: Balanced funds	11%	12%	8%	11%	14%	**18%**	4%
.9%	5: Munis	6%	16%	12%	13%	13%	8%	**20%**
12.0%	No discretionary financial assets	--	--	--	--	--	--	--
100.0%								

Table 5
Behavioral or Attitudinal Factors Included in Logit Regressions

Variable	Definition
Risk averseness	=1 if respondent is "not willing to take any financial risks", 0 otherwise
Shops around	Scale of 1-5, from "Almost no shopping" to "A great deal of shopping" for Investments
Economic pessimist	=1 if respondent expects U.S. economy to perform worse over next 5 years; else 0
Rates will rise	=1 if respondent expects interest rates in 5 years to be higher than today; else 0
Consults advisor	=1 if respondent gets information from a financial planner or broker; else 0
Short horizon	=1 if respondent has a financial planning horizon of a year or less; else 0
Saves for retirement	=1 if respondent considers retirement the most important reason for saving; else 0
Saves for emergencies	=1 if respondent considers emergencies the most important reason for saving; else 0
Saves for education	=1 if respondent considers children's education funding the most important reason for saving, 0 otherwise
Saves for family	=1 if respondent considers helping the family the most important reason for saving; else 0
Saves to buy house	=1 if respondent considers funding purchase of a house the most important reason for saving; else 0

Table 6
Effects of Demographic and Socio-Economic Variables on Cluster Membership

	Sign of Statistically Significant Logit Regression Coefficient, p<.05					
Cluster Number: Portfolio Orientation	Log Disc. Fin. Assets	Log Income	Ed.	HH Size	Male	Age
9: Cash	Neg	Pos	Pos	Neg	Pos	Pos
3: Savings	Pos	Neg	Neg	~	~	~
8: Cash & sav	Neg	~	~	~	~	~
4: Taxable bnd	Pos	~	~	Pos	~	Neg
2: Money mkts	~	~	~	~	~	~
6: Equities	Pos	Neg	~	~	~	~
1: Diversifier	Pos	Neg	Pos	~	~	~
5: Munis	Pos	~	~	~	~	~

~ indicates no statistically significant effect

For example, a household's wealth and income may predispose it to have an equity-dominant portfolio type, over-weighted in stocks. The financial advisor is likely to discover that the household is also more risk-tolerant than other households with more conservative portfolio orientations. If the advisor's goal is to optimize this client's asset allocation by reducing its exposure to the stock market, he or she should first recognize the client's inherent willingness to accept higher risk. The client's desire for additional information on his or her stock positions may be greater than his or her perceived need for a fixed income-oriented re-balancing. On the other hand, the household may also consider education funding to be a high priority investment goal but may not have computed the potential impact of a stock market downturn on its ability to meet this future obligation. The advisor could offer to guide the client through a quantitative assessment of this risk, proposing alternative portfolio allocations to mitigate it. The portfolio's asset class optimization could thus be presented as a personally relevant investment strategy and not an end in itself.

The specifics of this example were drawn from Tables 6 and 7. As seen in Table 6, membership in the Equity-oriented cluster is positively correlated with financial wealth, expressed as the log of the household's total discretionary financial assets but it is negatively associated with the log of income. The coefficients on education, household size, male sex, age, and retirement status do not compute as statistically significant. However, the Equity-oriented segment has three behavioral/attitudinal differentiators with non-zero coefficients, as shown in Table 7: risk averseness, with a negative coefficient, and the indication that retirement and education are top priority investment goals, both having positive coefficients.

In a similar fashion, a financial advisor beginning use of a formal asset allocation program with clients may be interested in the factors associated with a predisposition toward asset class diversification. As seen in Tables 6 and 7, the Diversifier cluster is differentiated by three socio-economic variables and two behavioral or attitudinal factors. Membership in this cluster is positively associated with the log of financial wealth, negatively associated with the log of income, and positively linked to educational attainment. The segment has a negative coefficient on risk tolerance, but positive on the *shops around* variable. In other words, members of the Diversifier cluster are likely to be better educated and more risk tolerant, but also to spend more time selecting their investments. Thus the financial advisor may find that serving this type of client can be time-intensive because of the complexity of the client's questions and the amount of comparison shopping done by the client.

Professional financial advisors can influence household investment behavior in ways other than the traditional client-advisor relationship. Their advice is offered at public appearances, on radio and television shows, in newspaper columns, public education courses at local high schools and community colleges, and other similar occasions. Advisors engaged in such activities may reach a lower-income, less-wealthy audience that is unable or unwilling to pay for individualized financial counsel. The logit results in Tables 6 and 7 can help advisors prepare for such endeavors by clarifying some portfolio allocation practices in these population segments.

As noted earlier, the cluster with the greatest number of households was the Cash-oriented cluster, containing approximately 32 million households. It is a common belief that such a portfolio allocation arises because the household lacks investable funds. The logit regression analysis performed here suggests a more complex explanation. The cluster's coefficient on the log of discretionary financial assets is indeed negative, indicating that the probability of a cash-oriented portfolio is greater among financially less-wealthy households. However, other demographic variables also have statistically significant coefficients. Membership in the Cash-oriented cluster is statistically more frequent among males and is positively related to age, educational attainment, and income. It is negatively associated with

Table 7
Effects of Behavioral and Attitudinal Factors on Cluster Membership

	Sign of Statistically Significant Logit Regression Coefficient, p<.05						
Cluster #: Portfolio Orient.	Risk averse	Shops around	Expect rates to rise	Uses Planner/ Broker	Saves for retirement	Saves for education	Saves for house
9: Cash	~	Negative	Positive	~	~	~	~
3: Savings	Positive	~	~	Negative	~	~	Positive
8: Cash & savings	~	~	~	~	~	~	~
4: Tax.able bonds	~	~	~	~	~	~	~
2: Money market	~	~	~	~	~	~	~
6: Equities	Negative	~	~	~	Positive	Positive	~
1: Diversifier	Negative	Positive	~	~	~	~	~
5: Municipal	~	~	~	Positive	~	~	~

~ indicates no statistically significant effect

household size. The risk tolerance coefficient does not compute as statistically significant, however cash-oriented households do appear less likely than others to shop around for investments and seem more likely to expect interest rates to rise. Thus financial advisors crafting messages for a less-wealthy audience may wish to emphasize the benefits and mechanics of comparison shopping for financial products.

The second most numerous portfolio orientation in 1995, comprising approximately 21 million households, was savings-oriented. In contrast to the Cash-oriented cluster, this segment's members are differentiated by a positive coefficient on the log of financial wealth and negative coefficients on the log of income and educational attainment. The Savings-oriented cluster also produces statistically significant positive coefficients on risk averseness and saving for a house and a negative coefficient on use of a financial planner or broker as an information source. Households with a savings-oriented portfolio may therefore be more receptive to information received from an FDIC-insured institution than a financial planner or financial planning organization.

It should be noted that in three cases – the Cash and savings, Taxable bonds, and Money markets-oriented clusters - statistical significance was not established for any of the tested behavioral or attitudinal coefficients. However, the logit model did find some of the socio-economic variables to be statistically significant. For the Cash and savings-oriented segment, the log of discretionary portfolio value had a statistically significant, negative coefficient. The Taxable bonds-oriented cluster had a negative age effect, but positive coefficients on the log of discretionary portfolio value and household size. The Money markets-oriented segment had a negative constant, but no statistically significant variable coefficients.

As mentioned above, the Savings-oriented segment seems less likely to consult with a financial planner or broker than other cluster members. The Muni-oriented segment, however, appears more likely to do so, since it is the only cluster to show a statistically significant, positive coefficient on the *uses planner/broker* variable. The Muni-oriented are also differentiated through a statistically significant, positive coefficient on the log of discretionary financial assets. This cluster is numerically the smallest, including less than an estimated one million households.

It may be appropriate to conclude this section with the observation that seasoned financial advisors might find the cluster analysis results somewhat less than enlightening. When describing them to audiences of financial industry professionals the author has encountered glances of emphatic agreement much more than moments of epiphany. However, the findings can be useful to financial advisors who are just beginning their careers, or who have not previously employed asset allocation methodologies in their work. To them, this article describes the types of portfolios they are likely to see among their current and prospective clients, as well as some of the distinguishing socio-economic and behavioral/attitudinal features that differentiate their users.

While each financial advisor may develop a unique client base, it would be helpful to know in general terms the cluster breakdown of that portion of the general population that turns to financial planners or brokers (Table 8). Approximately 11% of households indicated a planner or broker as an information source on investments. Of these, 56% have portfolios concentrated in FDIC-insured, constant-dollar type investments. Another 8% have portfolios dominated by money market accounts or funds. Hence it would appear that a beginning financial planner should anticipate a relatively high incidence of clients inexperienced in the use of equities as a primary investment vehicle. Educational approaches and communications strategies developed for these segments would offer considerable economies of scale.

Table 8
Portfolio Orientation of Respondents Indicating Financial Planner or Broker as Information Source

Portfolio Orientation	% of HHs
Cash	26
Savings	22
Diversified	12
Equities	10
Cash & savings	8
Money markets	8
Taxable bonds	7
Balanced funds	3
Munis	2

Base: 11% of all respondents, weighted.

Implications for Future Research

Despite the inclusion of 18 demographic, socio-economic, behavioral, and attitudinal variables, the logistic regression models of cluster membership performed poorly when used as predictors of cluster membership within the sample, with one exception - the Cash-oriented segment, where 60% of the cases were correctly classified. For all other segments the classification rate was 3% or less. This suggests that factors absent from the logit model may play an important role in determining an individual household's portfolio orientation. For example, the observation made by Ioannides (1992) and others of persistence in investment behavior suggests that a prior ownership experience in a financial product category may pre-dispose a household to future investments of the same type, thus leading to an overweighting of the portfolio in the corresponding asset class. Future research might explore the dynamic of this process in greater detail.

There is also a temptation to infer longitudinal, life cycle trends from the point-in-time, cross-sectional data contained in the 1995 Survey of Consumer Finances. For example, the logistic regressions computed a statistically significant, negative age effect for membership in the Taxable bonds cluster and a significant, positive age effect for the Cash-oriented cluster. Other things being equal, it would appear that a taxable bond-oriented portfolio is more likely at early stages of the life cycle and that a cash-oriented one is more likely at later life stages. Unfortunately, such a conclusion may not be warranted until one has corrected for cohort effects. It may be that older households in 1995 simply had a lower incidence of taxable bond-oriented portfolios to begin with. Perhaps their investment philosophy was more intensely affected by bond market volatility in 1987 than for other cohorts. To clarify these issues, future research might focus on identifying trends in household portfolio allocations over time, using multiple cross-sectional data sets collected at different points in time.

Finally, because of the absence of data on the asset class composition of the respondent's self-directed retirement plan accounts, this analysis could not determine if households employ similar portfolio allocations for their retirement accounts as they do for their non-retirement portfolios. Preliminary evidence (Sprudzs, 1996) from affluent household research suggests that combining IRA, Keogh, and 401(k) account data with non-retirement account data produces cluster analysis results analogous to those reported here. Researchers may wish to investigate this issue using public domain data representative of the general population, especially since some Social Security reform proposals include a provision for creating self-directed, separate accounts. At least one state university retirement system - Illinois, whose participants do not pay into Social Security, is offering such an option beginning in the latter half of 1998.

References

Blume, M. & Friend, I. (1975, May). The asset structure of individual portfolios and some implications for utility functions. *The Journal of Finance*, 2: 585-603.

Eller, T. J. (1994, January). Household wealth and asset ownership: 1991. *U.S. Bureau of the Census, Current Population Reports, Series P-70, No. 34.* Washington D.C.: U.S. Government Printing Office.

Everitt, B. (1993). *Cluster Analysis, Third edition.* New York: John Wiley & Sons Inc.

Feldstein, M. (1976, July). Personal taxation and portfolio composition: an econometric analysis. *Econometrica*, 4: 631-50.

Gunnarsson, J. & Wahlund, R. (1997). Household financial strategies in Sweden: an exploratory study. *Journal of Economic Psychology*, 18: 201-33.

Haliassos, M. & Bertaut, C. (1995, September). Why do so few hold stocks? *The Economic Journal*, 105: 1110-29.
Hochguertel, S., Alessie, R. & van Soest, A. (1997). Savings accounts versus stocks and bonds in household portfolio allocation. *Scandinavian Journal of Economics*, 1: 81-97.
Hubbard, R. G. (1985, February). Personal taxation, pension wealth, and portfolio composition. *The Review of Economics and Statistics*, 2: 53-60.
Ioannides, Y. M. (1992). Dynamics of the composition of household asset portfolios and the life cycle. *Applied Financial Economics*, 2: 145-59.
Johnson, B. W. (1998). Personal wealth, 1992-1995. *Internal Revenue Service Statistics of Income Bulletin,* Volume 17, 3: 70-95.
Kaiser, R. W. (1990). Individual investors. In J. Maginn & D. Tuttle (Eds.), *Managing investment portfolios, a dynamic process*, (3/1-3/46).
Kennickell, A. (1997). *Codebook for 1995 Survey of Consumer Finances*. Washington D.C.: Board of Governors of the Federal Reserve System.
Kennickell, A. B., Starr-McCluer, M. & Sundén, A. (1997, January). Family finances in the U.S.: recent evidence from the Survey of Consumer Finances. *Federal Reserve Bulletin*, *83* (1), 1-24.
King, M. A. & Leape, J. I. (1987, September). Asset accumulation, information, and the life cycle. *NBER Working Paper Series,* Working Paper No. 2392.
Lease, R. C., Llewellen, W. G. & Schlarbaum, G. G. (1976, September-October). Market segmentation: evidence on the individual investor. *Financial Analysts Journal,* 5: 53-60.
McGee, S. (February 4, 1998). Investment pros missed the boat on bond surge. *Wall Street Journal,* C1.
Montalto, C. P. & Sung, J. (1996). Multiple imputation in the 1992 Survey of Consumer Finances. *Financial Counseling and Planning*, 7: 133-46.
Papke, L., Peterson, Mitchell & Poterba. (1993). Did 401(k) plans replace other employer-provided pensions? . *NBER Working Paper Series,* Working Paper No. 4501.
Punj, G. & Stewart, D. W. (1983, May). Cluster analysis in marketing research: review and suggestions for application. *Journal of Marketing Research, 20:* pp. 134-48.
Riley, W. B. Jr. & Chow, K. V. (1992, November-December). Asset allocation and individual risk aversion. *Financial Analysts Journal*, 15-20.
SAS Institute Inc. (1989). *SAS/STAT User's Guide, Version 6, Fourth Edition, Volume 1*. Cary, NC: SAS Institute, Inc.
Skinner, J. (1992, January). Individual retirement accounts: a review of the evidence. *Tax Notes*, 54: 201-12.
Sprudzs, U. (1996, November-December). Personal investing styles among affluent households. *Bank Securities Journal Supplement*, 5: 10-12, 32.
StatSoft, Inc. (1997). STATISTICA for Windows [Computer program manual]. Tulsa, OK: StatSoft, Inc.
Thaler, R. (1994, May). Psychology and savings policies. *AEA Papers and Proceedings*, 2: 186-92.
Uhler, R. S. & Cragg, J. G. (1971). The structure of the asset portfolios of households. *Review of Economic Studies,* 38: 341-57.
Wang, H. & Hanna, S. (1997). Does risk tolerance decrease with age? *Financial Counseling and Planning, 8*(2): 27-31.
Weagley, R. O. & Gannon, C. F. (1991). Investor portfolio allocation. *Financial Counseling and Planning,* 2: 131-54.
Wiegold, C. F. (Ed.) (1997). *The Wall Street Journal Lifetime Guide to Money*. New York: Dow Jones.
Xiao, J. J. (1996). Effects of family income and life cycle stages on financial asset ownership. *Financial Counseling and Planning*, 7: 22-30.
Xiao, J. J. (1995). Patterns of household financial asset ownership. *Financial Counseling and Planning,* 6: 99-106.

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