A DATA MINING APPROACH TO CLIENT RISK TOLERANCE

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ABSTRACT: *Proper asset allocation advice given by money managers is dependent upon two inputs: (1) expected capital market returns and (2) the individual client's desire and ability to tolerate risk. Though much has been done to explain capital market returns, little has been added to our understanding of the factors which influence client risk tolerance. This paper proposes a quantitative approach to defining individual risk tolerance as well as an early attempt to determine both a predictive and normative approach.*

INTRODUCTION

Proper asset allocation advice given by money managers is dependent upon two inputs: (1) expected capital market returns and (2) the individual client's desire and ability to tolerate risk. Though much has been done to explain capital market returns, little has been added to our understanding of the factors which influence client risk tolerance.

As money managers begin the task of allocating a client's money into various investment vehicles they face two potential problems. First, the money manager may poorly allocate the funds. This can lead to the client either not having the required funds at a desired point in the future, or perhaps lead to a loss of client wealth. The second problem stems from the first; the money manager may be held liable for poor performance. This research study provides insight into the variables which determine money manager perception of client risk tolerance in a manner which addresses both problems. In addition, this paper presents two data mining methods for predicting a given client's risk tolerance level. The methodology presented provides both quantitative and qualitative models for measuring the perceived level of risk tolerance Chartered Financial Analysts, Certified Financial Planners, Certified Public Accountants, and Investment Professors as they undergo the process of advising clients. Thus, the research contributes a vehicle which allows clients to achieve their objectives, as well as one which provides the money manager with a technique to determine client risk tolerance in a manner which is both prudent and defendable.

LITERATURE REVIEW

Since the pioneering work of Markowitz and Sharpe, a major tenet of financial theory has been the proper definition of the risk/return relationship that exists in the capital markets. The same risk/return relationship extends to the process of individual asset allocation as well.

Individual asset allocation is a twofold process. First, the expected capital market returns must be specified. Second, the risk tolerance of the client must be determined. The question then arises as to the allocation of assets associated with the level of risk appropriate to a given investor's risk/return profile. While proper measurement of client risk tolerance is essential for suitable asset allocation, risk tolerance studies to date typically relate risk measures to the market, but do not investigate proportions of financial resources to be invested in the various assets.

The state of research in the risk tolerance area is best described by Harlow and Brown:

> "..It is surprising to find an almost total absence of unanimity about the proper assessment method. In fact, even a cursory inspection of the literature indicates that this area is seldom addressed with the same degree of rigor as is the analysis of the capital market side of the asset allocation equation."

The few studies that do address risk tolerance of investors exist in the form of an ongoing debate between psychologists and economists. Psychologists tend to believe, "that individuals' choices are primarily determined by factors unique to the particular decision setting." Hence, psychological studies approach the measurement of risk tolerance through the development of techniques which classify individuals into various risk categories. From these category assignments, the money manager derives insight into the risk attributes of the person and thus recommends an asset mix for their portfolio. Examples of this type of approach are detailed by Kaiser, Lipper and Busby, Droms, and Lebaron, Farrelly, and Gula. As pointed out by Cochrane:

> "The one input to the optimal portfolio advice is risk tolerance, and many providers of investment services have started thinking about how to measure risk tolerance using questionnaires. This is the trickiest part of conventional advice, in part since conventional measures of risk tolerance often seem quite out of whack with risk aversion displayed in asset markets. However, the basic question is whether one is more risk tolerant or less risk tolerant than the average investor. This question is fairly easy to conceptualize and can lead to a solid *qualitative, if not quantitative, answer*." (italics added)

On the other hand, economists "assume that there is some individual-specific mechanism playing a common role in all economic decisions." Hence, they assume client risk tolerance to be a function of variables which quantify client wealth. Examples of this are given by the well known Pratt and Arrow measures of risk aversion, and indicate that the typical investor will have a constant to declining risk premium as wealth increases.

Should gender impact risk tolerance? The fundamental question for advisors is whether, all things held constant, should men be assigned greater risk in their portfolios than women. Without answering the question of why this is done, the one sure result over time has been men having larger stock allocations and thus generating over time greater wealth. An equally perplexing question to be answered is why men would be assumed to be more tolerant of risk that women. Over the years, studies delving into risk tolerance have come to different conclusions. Numerous studies have found men willing to take more risk than women (see Hallahan, Faff & McKenzie, Grable & Lytton, and Sung & Hanna for a good discussion of this view). Still other studies have found that no relationship between gender and risk tolerance (see Grable& Joo, and Hanna, Gutter & Fan).

THEORY

This research advances a quantitative model of risk tolerance which incorporates features of both the psychological and economic paradigms. The model hypothesizes client risk tolerance to be a function of demographic and financial factors related to the client, e.g. time horizon, salary, age, gender, marital status and number of children, as well as demographic factors related to the investment advisor, e.g. age, gender, years of experience, designations held, etc.

Time horizon is often thought to be the most important variable affecting risk tolerance in the asset allocation process. The fundamental logic underlying this hypothesis is the longer the time period between initial investment and need for monies from the portfolio, the greater the probability the client can recoup any temporary loss in wealth. Therefore greater risk (with its promise of greater returns) can be assumed by the portfolio.

Client risk tolerance should also be an increasing function of the client's salary level, as clients with higher salaries should be capable of tolerating a short term loss of principal. Hence they should be capable of accepting higher risk within the portfolio.

Studies that have addressed the effect of gender on client risk tolerance have concluded that men tend to seek out greater risk than do women. A gender variable is included in this analysis to test this hypothesis.

Additional demographic factors included in the model relative to the hypothetical client are marital status and number of children. Being married, divorced, widowed, and/or having children are factors hypothesized to reduce the risk tolerance of the client. Thus, as marital status changes from that of being single to some other, and/or as the number of children increases, the risk tolerance of the client should decrease.

As indicated above, the perceived ability of a client to handle a specified level of risk may be a function of not only the demographic and financial circumstances of the client, but also demographic circumstances of the investment advisor. It is hypothesized that client risk is a decreasing function of advisor's age and perhaps a function of the advisor's gender.

PROPOSED METHODOLOGY

The database consists of responses from a geographically diverse survey of 4000 Chartered Financial Analysts (CFA), Certified Financial Planners (CFP), Certified Public Accountants (CPA), and investment professors (Ph.D.). A thousand surveys were mailed to each group of investment professionals and academics. Each received three hypothetical client scenarios and asked to provide the asset allocation they would recommend.

The client scenario included both demographic and financial information. The investment options given the respondents were U.S. equities, U.S. bonds, and/or cash equivalents. The survey respondents are also asked to provide their own demographic information. A sample of the survey mailed is included in the appendix.

Using the recommended asset allocations from the survey as inputs, an **implied** risk for each client scenario was calculated using a three asset standard deviation, suggested by the work of Harry Markowitz. The formula for the implied risk measure follows:

Equation 1

$$ó_{p,i} = [w_c^2 ó_c^2 + w_b^2 ó_b^2 + w_e^2 ó_e^2 + 2w_c w_b cov_{c,b} + 2w_c w_e cov_{c,e} + 2w_b w_e cov_{b,e}]^{½}$$

where:

$ó_{p,i}$	=	Implied perceived portfolio risk tolerance of hypothetical investor, i.
w_c	=	Recommended proportion invested in cash.
w_b	=	Recommended proportion invested in bonds.
w_e	=	Recommended proportion invested in equities.
$ó_c$	=	Standard deviation of cash returns.
$ó_b$	=	Standard deviation of bond returns.
$ó_e$	=	Standard deviation of equity returns.
$cov_{i,j}$	=	Covariance between returns of assets i and j.

The standard deviation and covariance statistics used in Eqn. 1 are estimated using five years of monthly returns from the current Ibbotson Associates Yearbook. Together with the standard deviation and covariance estimates provided therein, the asset allocations provided by the respondents allow for the direct measurement of the implied client risk tolerance, $ó_{p,i}$.

Insight into the variables that affect the perceived risk tolerance of an advisor and an individual investor can be derived using regression techniques. The implied risk, $ó_{p,i}$, of each hypothetical client is hypothesized to be a function of both the demographic/financial data associated with each hypothetical client, as well as the demographic data of the respondent.

Following the model advanced above, the specification of implied risk is as follows:

$ó_{p,i}$ = f (Client Demographics, Client Monies, and Advisor Demographics)

FINDINGS

The focus of this research is to identify the role gender plays in the financial planning process. In a normative sense, it should not matter whether the client is male or female, and the gender of the financial planner should play no role. To study this question, regression models were run for: (1) all advisors (male and female), (2) male advisors only, and then (3) female advisors only. In addition, separate regressions were run which: (1) included only client information (the reader should note a “cl” in front of those variables), and (2) included both client and advisor information (the reader should note an “adv” in front of the advisor variables). The reader is directed to the appendix of this paper. Tables 1 – 9 contain the data and regression output for this paper.

Table #10 (below) shows the variables significant in determining client risk tolerance when only client information and demographics are allowed into the regression models.

Table #10: Significant Variables - Client Information Only

Variable	All Advisors	Male Advisors	Female Advisors
Intercept	X	X	X
clage	X	X	X
clrace	X	X	
clfemale			
clmarried			
clincome	X	X	
clchildren			
clhoriz5	X	X	
clhoriz10			
clhoriz15	X	X	X
clhoriz20	X	X	
clinvest25k		X	X
clinvest50k		X	
clinvest100k			
clinvest500k			

Table #11 shows the variables that were significant in determining client risk tolerance when all client and advisor information are allowed into the regression models.

Table #11: Significant Variables - Client and Advisor Information Included

Variable	All Advisors	Male Advisors	Female Advisors
Intercept	X	X	X
clage	X	X	X
clrac	X	X	
clfemale			
clmarried			
clincome	X	X	
clchildre			
clhoriz5	X	X	
clhoriz10			
clhoriz15	X	X	X
clhoriz20	X	X	
clinvest25k	X	X	
clinvest50k	X		
clinvest100k			
clinvest500k			

AfricAmAdvi	X	X	
advFemale			
advage			
mariedadv			X

Three sets of regression models were estimated. All models have as the dependent variable the implied standard deviation (see Equation #1). The first set of regression models (see tables 2, 5, and 8 in the appendix) uses only client information as independent variables, the second set of regression models (see tables 3, 6, 9 in the appendix) uses both client information and advisor information. Parameter estimates are presented in the appendix of the paper. The yellow highlights show the significant variables.

All models tested had a significant Intercept. This is interpreted as indicating that some risk, perhaps the variability in T-Bill returns, is assumed by a client even when the client and the advisor are seeking to be completely risk averse.

Client age also proved significant in all models, with the sign negative. As client age increases the risk tolerance recommended by the advisor, and assumed by the client, tends to decrease. This would hold with prior beliefs that as clients get older, they should decrease the risk of their portfolio. The results shown indicate that the standard deviation of the clients' portfolios should decline by approximately .01% per year.

Client race was shown to be a significant factor when all advisors were included and when only the male advisors were included. The results for client race indicate that when male advisors are separated from their female counterparts, the issue of race becomes more significant and the variable's sign become more negative. The indication being that male advisors tend to recommend portfolios with less risk for African American clients. Though not the focus of this paper, it is worth noting that studies of African Americans indicate a lower allocation to stocks that for other groups. When only female advisors were studies, the race variable was not significant.

Income of a client appears significant when all advisor observations were included and when only male advisor observations were included. In both of these subsets, the sign of the coefficient is positive, indicating that as client income increases, risk tolerance is increased. This finding also corresponds to prior belief that as income (perhaps wealth) increases, clients and their advisors will (perhaps should) seek additional risk and the promise of greater return. When only female advisors are studies, the variable measuring client income is not significant. This finding does not conform to prior belief that client's with greater income should have the ability to tolerate greater risk.

Information as to client time horizon was also included in half the scenarios mailed. The horizons were indicated as 5, 10, 15, or 20 year horizons. In the models including all advisor data and in the models including only male advisors, the 5, 15, and 20 year horizons appear significantly different from having no time horizon specified. It is also interesting to note that the sign of the coefficient for the 5 year horizon is negative, but the sign for the 15 and 20 year horizons are positive. Indicating that the longer the time horizon the greater the risk tolerance of the investor. In the models which only considered female advisors, the only time horizon shown to be significant was the 15 year time horizon. For the female advisors the sign associated with the 15 year time horizon variable was positive (the same as male advisors) and had a higher positive sign.

Another factor tested in this study was the funds available for investing. The funds available in the scenarios were \$25,000, \$50,000, \$100,000, and \$500,000. When all advisors were considered, both the \$25,000 and \$50,000 investment levels proved significant. When only male advisors were considered, the \$25,000 investment level was significant. When only female advisors were considered, none of the investment levels were significant. The varied results make a conclusion somewhat difficult. However, it is interesting to note that the coefficients became much smaller as the funds available increased. Perhaps this indicates a tendency to increase risk tolerance as the amount of money available for investing increases.

The only variable found to be significant and uniquely related to female advisors was the marital status of the advisor. For reasons that are not clear, a married female financial planning advisor tends assign greater risk tolerance and therefore a larger equity allocation than female financial planners who are not married. There is no obvious interpretation for this; however, further research in this area would be justified.

WHAT SHOULD A CLIENT'S ASSET ALLOCATION BE?

The results above are interesting observations that may indeed change the way that risk tolerance is viewed. However, the more important question in financial planning is what the asset allocation should be for a particular client. Data Mining has some high potential tools for projecting the asset allocation for a particular client. Below is an introduction to these techniques and an analysis of the data used for the risk tolerance study above.

INTRODUCTION TO DATA MINING

Data mining is a general set of tools that come from two branches of research. One is from the statistical community and consists of computational statistics and multivariate modeling. The other is from the machine learning community and consists of artificial intelligence and computer science techniques that allow for the creation of non-parametric models. These non-parametric models generalize data into models that can be used for classification, pattern recognition, and ultimately prediction. One of the foremost benefits of using non-parametric models is that they can accommodate nonlinear behavior without loss of information.

There are several steps in any data mining project. First, an objective has to be created for the problem at hand. Usually, an exploratory analysis needs to be created to understand the available data. This is often done to avoid the "curse of dimensionality" that is often associated with large data sets. The "curse of dimensionality" refers to the exponential need for data as the number of dimensions of the data increases. Next, the data has to be transformed to an appropriate input form for the models under consideration. These transformations often involve converting the data into binary inputs. Next, the transformed data is used as input for the chosen data mining models. Lastly, the output of the models is analyzed and conclusions are reached. For further information on data mining the interested reader can see Han and Kamber, 2001, and Hand, et. al., 2001.

DATA MINING METHODOLOGY

Two data mining methods are applied to the survey data previously described (see page 4). First, a Kohonen Artificial Neural Network (K-ANN) is applied to extract insight into the risk tolerances of clients and to reduce the number of dimensions needed for analysis. The K-ANN is a clustering technique that attempts to separate the data into homogeneous groups. This produces output information in graphical form and is used for both finding and defining relationships between the variables. Second, a back-propagation neural network (BP-NN) is used for predictive purposes. This model produces predictive results that quantify the relationships within the data. Combined, these predictive methods provide both qualitative and quantitative predictive measures that can be used for asset allocation.

The survey data are transformed into an appropriate input form for both the K-ANN and the BP-NN. The actual models used here are presented in Rogers, 1997. For both models the data has to be normalized to ensure that one factor (dimension) does not dominate another factor. For instance, the client age factor ranges from 24 to 77 years whereas the number of client's number of children factor ranges from 0 – 4. For the K-ANN model, each of the factors is normalized to a range of 0 – 100. For example, a client that is 30 years old would have this factor transformed to the value 11 by using the formula:

normalized factor = ((age-minAge)/rangeOfAges) * 100
where:
normalized factor = transformed value
age = client's current age
minAge = minimum client age value found in the entire data set
rangeOfAges = maximum client age – minimum client age

The objective of using the K-ANN during the exploration process is to divide the data into clusters that give insight into the relationships within the data. An assumption in classification problems is that the data are separable into perfect classes. This may not always be the case but is often valid in exploratory data analysis.

The apparently clusters discovered using the K-ANN are shown in Figures 1, 2, and 3 in the appendix of this paper with a data dictionary that describes the categories used. There were a total of ten clusters created but most of the clusters did not indicate any significant relationships. The three main clusters created group the data into the following clusters with these main characteristics:

<u>Cluster 1:</u> Gender of Manager, IMM/PMM/OMM Designation, Marital Status of Client, Gender of Client and Income of Client (see appendix, Figure 1).

<u>Cluster 2:</u> Manager Age, IMM/PMM/OMM Designation, Education Level of MM, Client Age, Investment Amount (see appendix, Figure 2).

<u>Cluster 3:</u> Race of MM, Experience of MM, IMM/PMM/OMM Designation, Other Designations (CFA, CPA, CCM, CFM, Other), Number of Children of Client, Time Horizon of Client (see appendix, Figure 3).

These clusters are later used for input dimension reduction for the BP-NN and suggest the following general relationships within the data:

1. (from cluster 1) Married women with higher incomes tend to use money managers who are female (see appendix, Figure 1).
2. (from cluster 2) Older clients use older money managers and provide larger amounts of investments (see appendix, Figure 2).

3. (from cluster 3) Clients with longer time horizons tend to use money managers with multiple Other Designations (see appendix, Figure 3).

For the BP-NN model, each of the input and output values is normalized based on the average found for the given factor. For each factor, the average value is calculated and then, the individual values are compared against the average value for that factor. If the value is higher than the average value (for continuous variables), it is assigned a value of 1 and 0 otherwise. For categorical variables, the categories are split in half and the transformed values are assigned a 0 or a 1. For instance, the factor ClientJob has a possible value of 0-4. So, the values of 0, 1, and 2 are transformed into a 0 and the values 3 and 4 are transformed into a 1.

The objective of using the BP-NN is to produce quantitative predictive results for the allocation of a future client's portfolio. Using the past behavior of money managers the BP-NN creates a model that accepts as input the available factors, such as age and income, and outputs the portfolio allocation in terms of predicted equities, bonds and cash.

Using the transformed input data several configurations of the individual factors are used as input into the BP-NN. The three clusters previously discussed are used as input as well as the entire data set. Since the BP-NN has only a single output, the model is run three times for each input set – once for each of the output variables. The results are shown in Table 12 for each of the four model inputs. It can be seen that using each of the 18 dimensions of the data set performed better than any of the reduced input sets for both the equity and bond allocation prediction. Also, it is noted that the full data set did not perform quite as well as the reduced data sets for cash. This can be attributed to cluster models predicting amount of cash better due to the low average of allocated cash within the survey data. It is expected that the more difficult predictions would be for the equities and bond. This is shown in these results in Table 12.

Table 12: Percentage correctly predicted for the columns of the equities, bonds, and cash

	% Correctly Predicted		
	Equity	Bond	Cash
Cluster 1	55.8%	46.7%	71.8%
Cluster 2	54.9%	44.1%	73.1%
Cluster 3	55.4%	45.8%	73.1%
Full Data Set	65.3%	62.7%	62.7%

Table 13 shows the overall summary for the predictive capabilities of the four model configurations. It is seen that the model using the full data set has a much lower rate of predicting all three outputs incorrectly. Conversely, the full data set also has the highest correct predictions for both the 2 of 3 and 3 of 3 categories. This suggests that the model using the full data set is much more capable of predicting the output than any of the subset models attempted. Also, it suggests that there are complex relationships between many of the variables that cannot be explained without using the entire spectrum of the variables. The predictions using the full data set model predicted at least 2 of the 3 categories correctly 67.5% of the time whereas the reduced set models had a much lower success rate.

Table 13: Summary of the percentage correctly predicted for each data point

% Correctly Predicted					
	0 of 3	1 of 3	2 of 3	3 of 3	at least 2 of 3
Cluster 1	11.6%	32.4%	25.5%	30.3%	55.8%
Cluster 2	11.2%	34.1%	25.5%	29.0%	54.5%
Cluster 3	10.3%	33.7%	26.8%	29.0%	55.8%
Full Data Set	8.2%	24.2%	35.9%	31.6%	67.5%

CONCLUSION

It has been shown that proper asset allocation advice given by money managers is dependent upon two inputs: (1) expected capital market returns and (2) the individual client's desire and ability to tolerate risk. Though much has been done to explain capital market returns, little has been added to our understanding of the factors which influence client risk tolerance. This paper proposes a quantitative approach to defining individual risk tolerance as well as an early attempt to determine both a predictive and normative approach. Although the K-ANN did not produce significant results in the reduction of dimensions for the BP-NN, the BP-NN still performed admirably well at predicting the amount of risk tolerance for clients. This creates a much-needed vehicle which allows clients to achieve their objectives, as well as one which provides the money manager with a technique to determine client risk tolerance in a manner which is both prudent and defendable.

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APPENDIX

The MEANS Procedure

Variable	Label	Mean	Std Dev	Minimum	Maximum
USEquity	USEquity	56.505	23.623	0.000	100.000
USBonds	USBonds	30.779	19.462	0.000	100.000
Cash	Cash	12.691	16.802	0.000	100.000
AfricAmAdvi		0.073	0.261	0.000	1.000
advFemale	advFemale	0.126	0.331	0.000	1.000
advage	advage	48.272	10.084	24.000	77.000
advExperience	advExperience	16.414	9.858	0.000	45.000
mariedadv		0.835	0.371	0.000	1.000
clage	clage	44.852	15.179	20.000	76.000
clrace	clrace	0.492	0.500	0.000	1.000
clfemale	clfemale	0.481	0.500	0.000	1.000
clmarried	clmarried	0.501	0.500	0.000	1.000
clchildren	clchildren	1.612	1.146	0.000	4.000
clincome	clincome	47274.613	25206.798	10000.000	121400.000
deviation	deviation	0.027	0.009	0.001	0.045
clhoriz5		0.124	0.329	0.000	1.000
clhoriz10		0.120	0.325	0.000	1.000
clhoriz15		0.143	0.351	0.000	1.000
clhoriz20		0.108	0.311	0.000	1.000
clselfemp		0.289	0.453	0.000	1.000
statemp		0.280	0.449	0.000	1.000
majemp		0.294	0.456	0.000	1.000
retired		0.136	0.343	0.000	1.000
clinvest25k		0.231	0.422	0.000	1.000
clinvest50k		0.257	0.437	0.000	1.000
clinvest100k		0.265	0.442	0.000	1.000
clinvest500k		0.123	0.328	0.000	1.000
clinvest1m		0.124	0.329	0.000	1.000

Table 1: All Advisors

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	0.01342	0.00095826	15.16	<.0001
Error	901	0.05694	0.00006320		
Corrected Total	915	0.07036			

Root MSE	0.00795	R-Square	0.1907
Dependent Mean	0.02746	Adj R-Sq	0.1781
Coeff Var	28.94847		

Table 2: All Advisors

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	0.01427	0.00079301	12.68	<.0001
Error	897	0.05608	0.00006252		
Corrected Total	915	0.07036			

Root MSE	0.00791	R-Square	0.2029
Dependent Mean	0.02746	Adj R-Sq	0.1869
Coeff Var	28.79338		

Table 3: All Advisors

The MEANS Procedure

Variable	Label	Mean	Std Dev	Minimum	Maximum
USEquity	USEquity	56.991	23.086	0.000	100.000
USBonds	USBonds	30.589	19.087	0.000	100.000
Cash	Cash	12.391	16.623	0.000	100.000
AfricAmAdvi		0.076	0.265	0.000	1.000
advage	advage	48.726	10.249	24.000	77.000
advExperience	advExperience	16.748	10.143	0.000	45.000
mariedadv		0.870	0.337	0.000	1.000
clage	clage	44.608	15.145	20.000	76.000
clrace	clrace	0.497	0.500	0.000	1.000
clfemale	clfemale	0.486	0.500	0.000	1.000
clmarried	clmarried	0.487	0.500	0.000	1.000
clchildren	clchildren	1.574	1.133	0.000	4.000
clincome	clincome	46983.715	25413.634	10000.000	121400.000
deviation	deviation	0.028	0.009	0.001	0.045
clhoriz5		0.127	0.333	0.000	1.000
clhoriz10		0.125	0.331	0.000	1.000
clhoriz15		0.150	0.357	0.000	1.000
clhoriz20		0.110	0.313	0.000	1.000
clselfemp		0.299	0.458	0.000	1.000
statemp		0.279	0.449	0.000	1.000
majemp		0.298	0.458	0.000	1.000
retired		0.124	0.330	0.000	1.000
clinvest25k		0.244	0.430	0.000	1.000
clinvest50k		0.259	0.439	0.000	1.000
clinvest100k		0.241	0.428	0.000	1.000
clinvest500k		0.127	0.333	0.000	1.000
clinvest1m		0.129	0.335	0.000	1.000

Table 4: Male Advisors Only

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	0.01119	0.00079894	12.72	<.0001
Error	789	0.04955	0.00006280		
Corrected Total	803	0.06073			

Root MSE	0.00792	R-Square	0.1842
Dependent Mean	0.02758	Adj R-Sq	0.1697
Coeff Var	28.73567		

Table 5: Male Advisors Only

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	0.01219	0.00071713	11.61	<.0001
Error	786	0.04854	0.00006176		
Corrected Total	803	0.06073			

Root MSE	0.00786	R-Square	0.2007
Dependent Mean	0.02758	Adj R-Sq	0.1835
Coeff Var	28.49665		

Table 6: Male Advisors Only

The MEANS Procedure

Variable	Label	Mean	Std Dev	Minimum	Maximum
USEquity	USEquity	53.795	25.858	0.000	100.000
USBonds	USBonds	31.259	21.333	0.000	100.000
Cash	Cash	14.938	18.104	0.000	100.000
AfricAmAdvi		0.067	0.251	0.000	1.000
advage	advage	45.336	8.398	28.000	64.000
advExperience	advExperience	14.011	7.078	0.000	30.000
mariedadv		0.723	0.450	0.000	1.000
clage	clage	45.076	15.312	20.000	70.000
clrace	clrace	0.462	0.501	0.000	1.000
clfemale	clfemale	0.454	0.500	0.000	1.000
clmarried	clmarried	0.597	0.493	0.000	1.000
clchildren	clchildren	1.773	1.217	0.000	4.000
clincome	clincome	49238.235	24304.272	13500.000	121400.000
deviation	deviation	0.027	0.009	0.001	0.045

clhoriz5	0.076	0.266	0.000	1.000
clhoriz10	0.084	0.279	0.000	1.000
clhoriz15	0.118	0.324	0.000	1.000
clhoriz20	0.101	0.302	0.000	1.000
clselfemp	0.210	0.409	0.000	1.000
statemp	0.286	0.454	0.000	1.000
majemp	0.303	0.461	0.000	1.000
retired	0.202	0.403	0.000	1.000
clinvest25k	0.134	0.343	0.000	1.000
clinvest50k	0.235	0.426	0.000	1.000
clinvest100k	0.420	0.496	0.000	1.000
clinvest500k	0.109	0.313	0.000	1.000
clinvest1m	0.101	0.302	0.000	1.000

Table 7: Female Advisors Only

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	0.00300	0.00021462	3.19	0.0004
Error	97	0.00653	0.00006734		
Corrected Total	111	0.00954			

Root MSE	0.00821	R-Square	0.3151
Dependent Mean	0.02663	Adj R-Sq	0.2162
Coeff Var	30.81294		

Table 8: Female Advisors Only

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	0.00336	0.00019767	3.01	0.0004
Error	94	0.00618	0.00006570		
Corrected Total	111	0.00954			

Root MSE	0.00811	R-Square	0.3524
Dependent Mean	0.02663	Adj R-Sq	0.2353
Coeff Var	30.43653		

Table 9: Female Advisors Only

Dimension	
1	race
2	gender
3	age

4	Experience	
5	IMM	
6	PMM	
7	OMM	
8	Education	
9	SumDesignations -	Sum of all designations of the money manager
10	MaritalStatus	
11	ClientAge	
12	ClientSex	
13	ClientMarried	
14	ClientChildren	
15	ClientIncome	
16	ClientInvestmentAmount	
17	TimeHorizon	
18	Expectancy	

Table 10: Data Dictionary for the Dimensions within each of the Clusters.

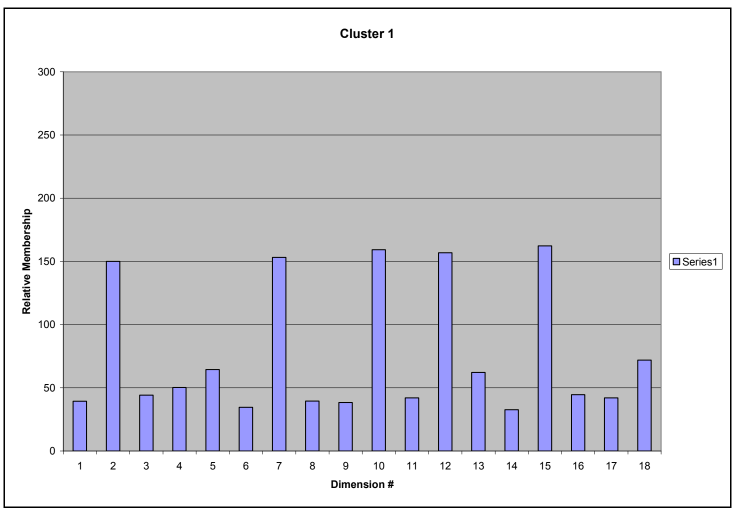

Figure 1: Dimensions from Cluster 1 illustrated.

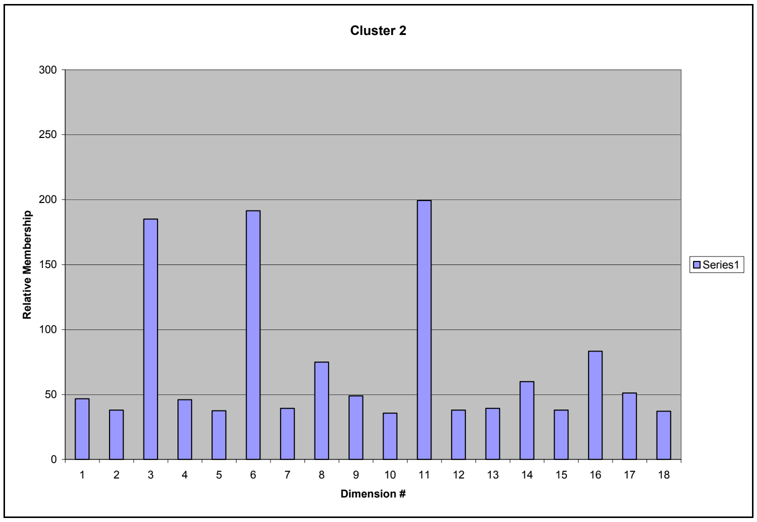

Figure 2: Dimensions from Cluster 2 illustrated.

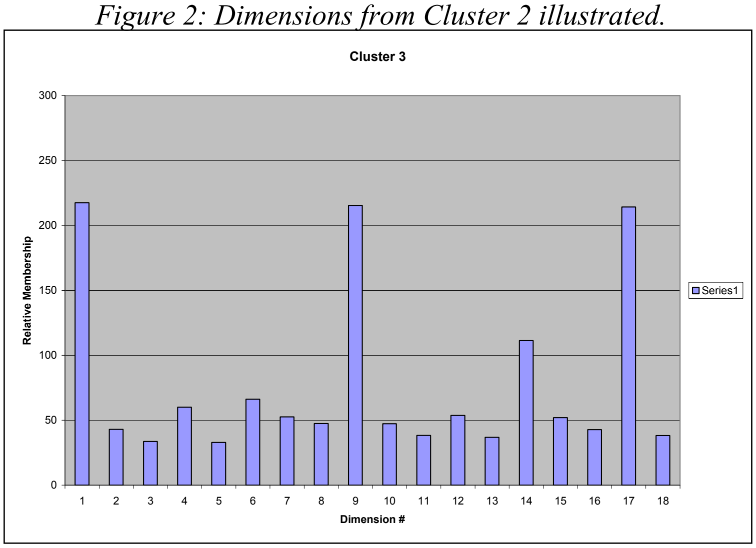

Figure 3: Dimensions from Cluster 3 illustrated.