

INVESTOR RISK TOLERANCE:
TESTING THE EFFICACY OF DEMOGRAPHICS
AS DIFFERENTIATING AND CLASSIFYING FACTORS

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(ABSTRACT)

This study was designed to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. The Leimberg, Satinsky, LeClair, and Doyle (1993) financial management model was used as the theoretical basis for this study. The model explains the process of how investment managers effectively develop plans to allocate a client's scarce investment resources to meet financial objectives.

An empirical model for categorizing investors into risk-tolerance categories using demographic factors was developed and empirically tested using data from the 1992 Survey of Consumer Finances (SCF) ($N = 2,626$). The average respondent was affluent and best represented the profile of an investment management client.

Based on findings from a multiple discriminant analysis test it was determined that respondent demographic characteristics were significant in differentiating among levels of risk tolerance at the $p < .0001$ level (i.e., gender, married, single but previously married, professional occupational status, self-employment status, income, White, Black, and Hispanic racial background, and educational level), while three demographic characteristics were found to be statistically insignificant (i.e., age, Asian racial background, and never married). Multiple discriminant analysis also revealed that the demographic variables examined in this study explained approximately 20% of the variance among the three levels of investor risk tolerance.

Classification equations were generated. The classification procedure offered only a 20% improvement-over-chance, which was determined to be a low proportional reduction in error. The classification procedure also generated unacceptable levels of false positive classifications,

which led to over classification of respondents into high and no risk-tolerance categories, while under classifying respondents into the average risk-tolerance category.

Two demographic characteristics were determined to be the most effective in differentiating among and classifying respondents into risk-tolerance categories. Classes of risk tolerance differed most widely on respondents' educational level and gender. Educational level of respondents was determined to be the most significant optimizing factor. It also was concluded that demographic characteristics provide only a starting point in assessing investor risk tolerance. Understanding risk tolerance is a complicated process that goes beyond the exclusive use of demographic characteristics. More research is needed to determine which additional factors can be used by investment managers to increase the explained variance in risk-tolerance differences.

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CHAPTER I

INTRODUCTION AND STATEMENT OF THE PROBLEM

The purpose of this study was to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance¹ and classify individuals into risk-tolerance categories. In recent years, investment managers² and researchers have taken a renewed interest in understanding investor risk tolerance. Much of this interest has coincided with advances in the conceptualization of investment management models. Modern investment management decision making models require investment managers to use, at a minimum, four factors as inputs into the development of financial and investment plans. These inputs include an investor's: (a) goals, (b) time horizon, (c) financial stability, and (d) risk tolerance (Garman & Fogue, 1997; Hallman & Rosenbloom, 1987; Trone, Allbright, & Taylor, 1996).

The first three inputs (i.e., goals, time horizon, and financial stability) tend to be objective and relatively easy to measure. Investor goals include plans to use investment principal and earnings for purposes such as educational expenses, retirement, future gifts, and estate transfers. Time horizon refers to the anticipated time span the investor will need before beginning to use investment returns; financial stability refers to concepts such as the nature and stability of an investor's employment, assets, liabilities, and net worth, and the extent to which current income is needed for current living expenses. The fourth input, investor risk tolerance, refers to how well an investor is able "to weather the ups and particularly the downs in the securities markets ... with an emphasis on an investor's attitudes and emotional tolerance for risk" (Hallman & Rosenbloom,

¹ The term risk is defined in the investment industry in terms of performance variance or volatility (Trone et al., 1996). Risk that refers to variability or volatility of returns is called investment risk. Investment risk consists of six primary elements: a) liquidity risk, b) purchasing power risk, c) funding risk, d) risk/return tradeoff risk, e) asset allocation risk, and f) opportunity cost risk. The term investor risk tolerance refers to an investor's comfort associated with investment variability or volatility (Schaefer, 1978). See Trone et al. for a thorough discussion of these investment risks.

² An investment manager was defined in this research as a financial planner or investment advisor. Financial planners and investment advisors are individuals who are paid to "advise clients about personal finances. He or she has usually undergone training and has met the qualifications for particular professional certifications" (Garman & Fogue, 1997, p. G10).

1987, p. 169). Unlike the other inputs into the investment management decision making process, investor risk tolerance tends to be subjective rather than objective, and somewhat difficult to measure.³ Although difficult to measure, Trone et al. (1996) have suggested that an ability to achieve desired investment objectives is influenced most significantly by an investor's emotional ability to accept possible losses in portfolio value.

Due to the subjective nature of investor risk tolerance, sometimes investment managers “give only lip service to analyzing one's level of financial risk tolerance” (Roszkowski, 1995, p. RT 1). According to Roszkowski, Snelbecker, and Leimberg (1993), analyzing an investor's risk tolerance has tended to be based on demographics, which have been turned into risk predicting heuristics.⁴ The following heuristics, based entirely on demographics, continue to be widely used to separate people into high, average, and no risk-tolerance categories (Roszkowski et al.):

- (a) females are less risk tolerant than males;
- (b) decreasing risk tolerance is associated with increasing age;
- (c) unmarried individuals are more risk tolerant than are married individuals;
- (d) individuals employed in professional occupations, rather than non-professional occupations, tend to be more risk tolerant;
- (e) self-employed individuals are more risk tolerant than those employed by others;
- (f) risk tolerance increases with income;

³ Although the importance of quantifying and understanding individual investor risk tolerance is recognized as a key input into the investment management decision making process, “most everything one reads in the financial press and in the glossy publications of money managers and mutual funds still touts investment returns, with rarely a comment about the risk taken” (Trone et al., 1996, p. 73). This emphasis on returns rather than risk may be the result of the subjective nature of investor risk tolerance. Some investors fail to measure risk, and when they do, they often use demographics, in the form of risk-tolerance rules-of-thumb (e.g., men are more risk-tolerant than women and older individuals are more risk-averse than younger persons), as predictors of investor risk tolerance.

⁴ The term “heuristics” is often used to describe mental strategies that people use to reduce difficult tasks to simpler judgments (Deacon & Firebaugh, 1988; Fischhoff, Slovic, & Lichtenstein, 1979). According to Payne (1973), “individuals find it difficult to process information and therefore employ decision strategies designed to reduce the information processing load” (p. 440). As is the case when dealing with investor risk tolerance, heuristics may be useful in certain situations, but in other circumstances heuristics can lead to “errors that are large, persistent, and serious in their implications” (Fischhoff et al., p. 19). Researchers, such as Heisler (1994), have suggested that frequently individuals are not aware that they are making poor decisions when using risk-tolerance heuristic judgments.

- (g) Whites are more risk tolerant than non-Whites; and
- (h) risk tolerance increases with education.

Classifying Investors Into Risk-Tolerance Categories: The Costly Effects

Investment managers have a fiduciary responsibility to take into account investor risk tolerance when developing investment strategies and plans (Garman & Fogue, 1997; Hallman & Rosenbloom, 1987; Trone et al., 1996). There is general consensus among investment managers that demographics can be used to adequately classify clients into investor risk-tolerance categories. This consensus is alarming, because there is evidence to suggest that relying primarily on demographics to classify investors into risk-tolerance categories may cause investment managers to create and implement investment management plans that ultimately fail to match a client's investment objectives (Heisler, 1994; Palsson, 1996; Trone et al., 1996).

Age, the most widely used demographic factor for differentiation and classification purposes, provides a good example of this potential problem. Investment managers assume that age and risk tolerance are inversely related. Thus, older investors are usually classified as tolerating only low levels of investment risk, while younger investors are assumed to prefer higher levels of investment risk. This classification strategy is costly in two respects. First, there is a chance that clients will be classified incorrectly, which can lead to extreme portfolio allocations for those clients. Second, this classification system may ultimately lead to what Palsson (1996) called a dispersion in wealth and welfare, because clients who are mis-classified may (a) sell at a loss if incorrectly classified into a higher risk-tolerance category, or (b) fail to meet goals and objectives if wrongly classified into a lower risk-tolerance category. In either case, the fiduciary credibility of an investment manager may be questioned.

It appears that Palsson's (1996) assertions are supported by investment manager performance. According to Train (1995), the average mutual fund returned 12.5% a year for the five year period ending in mid-1994, but the actual returns obtained by investors in these same funds was negative 2.2%. Quinn (1997) reported a similar finding. She reported that investors who owned equity mutual funds earned, on average, 10% less than the funds themselves in each

of the 12 years from 1984 to 1996. These results indicate that investors purchased shares when prices were rising, and sold shares when prices were falling.⁵

Poor investment performance on the part of investment managers suggests that managers may not be measuring investor risk tolerance accurately, and that investment managers may be relying on demographic classification factors that have limited or no differentiating efficacy. Findings reported by Train (1995) and Quinn (1997) also suggest that investment managers may be relying on demographics to classify individuals into investor risk-tolerance categories because they lack the tools, both models and heuristics, to accurately classify investors into risk-tolerance categories (Elvekrog, 1996). Regardless of the reasons, it appears that some investment managers systematically fail to choose investments that match underlying investor risk tolerances, which often results in costly losses⁶ (MacCrimmon & Wehrung, 1986; Palsson, 1996; Roszkowski, et al., 1993; Train).

Purpose and Justification of Study

It is not uncommon for investment managers to use certain demographics to classify investors into risk-tolerance categories when establishing investment management standards, controlling purchases and sales of investments, and managing overall client resources (Roszkowski et al., 1993). While possibly useful in certain circumstances, it has been shown that the use of demographics, when used as classification factors in determining investor risk tolerance, has not improved investment performance or household welfare, and in fact, the use of demographics has sometimes resulted in financial losses for investors (Palsson, 1996; Train, 1995). Research concerning the differentiating efficacy of certain demographics is inconclusive (e.g., Palsson; Sung & Hanna, 1996b). Furthermore, there is general consensus among researchers and investment managers that additional research concerning the usefulness of certain

⁵ Nearly 97% of total mutual fund sales during this time period were made by commissioned investment managers (Gibson, 1997).

⁶ Losses occur when an investor abandons an asset allocation plan or investment strategy “because of unwelcomed volatility” (Trone et al., 1996, p. 83). Investors will likely forfeit their chances of achieving desired investment objectives and abandon an investment program for its volatility of returns than for any other reason according to Trone et al. “Consequently, this manifestation of risk (i.e., aversion to losses) is the crucial parameter for the investor’s determination of an optimal asset allocation” (Trone et al., p. 83).

demographics in categorizing someone into a risk-tolerance category is needed (Baker & Haslem, 1974; Snelbecker, Roszkowski, & Cutler, 1990; Sung & Hanna; Williams, 1989).⁷

The purpose of this study was to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. Conclusions and recommendations based on findings from this research were developed to:

- (a) provide insights into which of the eight categories of demographics were most significant in differentiating among and classifying someone into investor risk-tolerance categories;
- (b) go beyond purely subjective criteria related to the personal characteristics of individuals in order to define a set of operating characteristics that distinguished among high, average, and no investor risk tolerance; and
- (c) consider the implications of those demographics that did not distinguish among high, average, and no investor risk tolerance.

It was anticipated that this research would be useful to investment managers in three specific ways. First, this research would add a measure of objectivity to a decision making process which has tended to rely on a combination of art, intuition, and experience in arriving at an estimate of investor risk tolerance. Second, this study would contribute to the general knowledge in the field of family financial management by providing a multivariate analysis of the risk-tolerance variable using the levels of response provided in the 1992 Survey of Consumer Finances (Sung & Hanna, 1996b); and third, this research would contribute to the ongoing discussion regarding the efficacy of using demographics for use in differentiating among and classifying investors into different risk-tolerance categories.

⁷ Researchers, such as Sung and Hanna (1996b), have called for a multivariate analysis of investor risk tolerance to determine what types of factors can be used to classify investors into risk-tolerance categories.

Research Question

The following research question was used to direct this study:

Can the variables gender, age, marital status, occupation, self-employment, income, race, and education be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories?

Conceptual Background and Framework

Investment managers are concerned primarily with a client's access to and allocation of investment and financial resources. The role of an investment manager is to help establish a client's financial objectives, develop plans, and manage how resources are accessed and allocated in meeting objectives. The investment manager's administrative role can be defined as managerial activities and processes taken to meet desired financial goals and purposes by using resources (Leimberg, Satinsky, LeClair, & Doyle, 1993).

Leimberg et al. (1993) were among the first to conceptualize the financial planning and investment decision making process (Figure 1). The Leimberg et al. financial management model offers investment managers and researchers a conceptualization of the activities involved in working through the investment planning process. The framework is useful as a working theoretical model because it is holistic, giving equal weight to inputs, management processes, and outputs. The model also offers researchers a theoretical view of how investment managers use background analysis information and objectives as inputs into the development of financial and investment plans, and how a process-centered management orientation leads to attained objectives. As such, the Leimberg et al. financial management framework was used as the conceptual model for this study. Specifically, this theoretical framework was used to test eight categories of demographics to determine if these characteristics could be used to differentiate among and classify individuals into investor risk-tolerance categories.

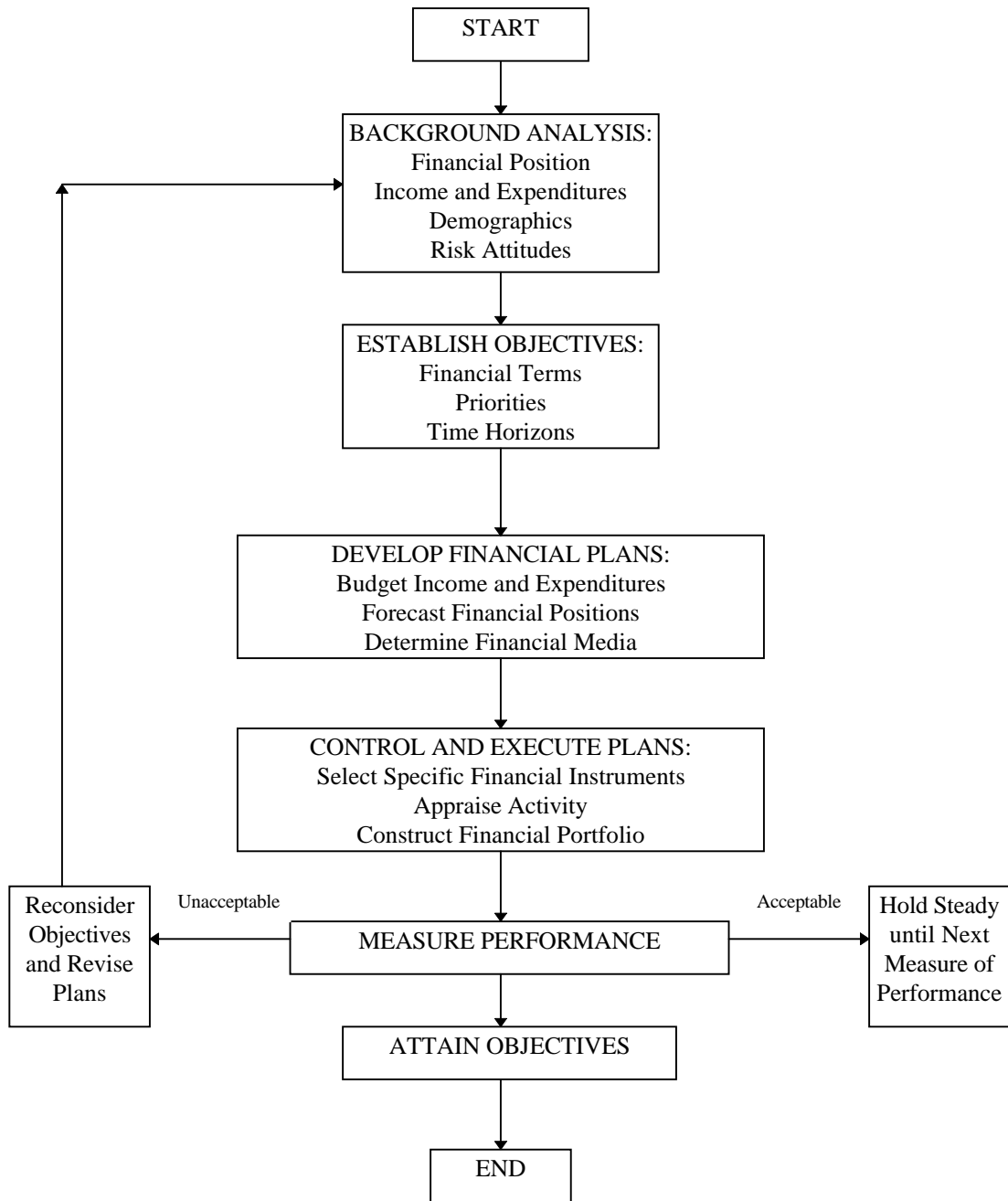


FIGURE 1
 Financial Management Model, Leimberg et al. (1993)

The Leimberg et al. (1993) framework (Figure 1) was developed to explain the process of how investment managers effectively develop plans to allocate scarce investment resources to meet financial objectives. The model is similar to frameworks used previously in family resource management. First, the model is conceptualized linearly; second, the model relies on inputs into a managerial process; and third, outputs are measured in terms of client satisfaction, which is defined as achieved ends in comparison with initial goals. Leimberg and his associates recommended using the framework as a working tool to help investment managers summarize the following individual activities involved in the process of investment and financial planning: (a) gathering background information, (b) establishing financial objectives, (c) developing financial plans, (d) controlling and executing plans, and (e) measuring performance.

Gathering background information entails obtaining information such as records of income and expenditures as well as a descriptive assessment of an individual's or family's financial position. This step in the management of investment decisions is important, because prior to setting objectives investment managers must obtain and understand objective and subjective information regarding demographic inputs. According to Leimberg et al. (1993), a necessary and "important area of background analysis has to do with attitudes toward the degree of risk someone is willing to accept in a financial plan. Feelings about investment risk, personal financial security, and independence are just as important as income statements or net worth" (p. 23). Investment managers who are aware of their clients' risk tolerance are best able to establish realistic and acceptable objectives. Leimberg et al. warned that investment managers who ignore risk tolerances are unlikely to implement plans or meet objectives.

As Figure 1 indicates, risk attitudes together with information concerning a client's financial position, income and expenditures, and certain demographics are required as inputs into the establishment of financial objectives. Setting investment objectives is one way of working toward an investment and financial plan. As Trone et al. (1996) and others (e.g., Garman & Forgue, 1997; Hallman & Rosenbloom, 1987) have indicated, background analysis and establishment of objectives encompass the four primary components that investment managers must use when creating an investment management strategy (i.e., goals, financial stability, time frame, and investor risk tolerance).

The step called “develop financial plans” in the Leimberg et al. (1993) framework is similar to the concept of developing an investment plan or investment management strategy as proposed by Trone et al. (1996) and others (Garman & Fogue, 1997; Hallman & Rosenbloom, 1987). The planning stage includes the budgeting of income and expenditures for both short- and long-term activities.

The next stage of the financial planning model, “control and execute plans,” involves setting the plan in motion. Controlling and executing plans should include determining the specific financial instruments (e.g., equities, bonds, commodities, etc.) that will be included in a portfolio to meet objectives. Activities during this stage of the investment management process also might include the purchase and sale of various assets, a review of life insurance needs, an analysis of liabilities, and the appraisal of other investment and financial planning occurrences.

Measuring performance is the step that requires investment managers to determine the progress they are making toward the attainment of objectives. This final step in the Leimberg et al. (1993) model requires a review of one’s

plans to see if they are still valid and an analysis of the financial environment to take note of unexpected changes. If one’s original objectives are no longer realistic and desirable, you will want to review and alter them. In that case your entire plan may have to be recycled through each of the stages described above. This model of financial planning is a dynamic one that is continually repeated as personal, financial, and environmental factors change (p. 25).

The use of frameworks similar to Leimberg et al.’s financial management model (i.e., frameworks that require inputs into a managerial function leading to outputs) in the realm of personal financial management research is not without precedent. For example, Deacon and Firebaugh (1988) provided readers with an entire chapter devoted to a systems discussion of family financial management. Mueller and Hira (1984) used a management systems framework to examine the influence of money management practices and socio-demographic characteristics on household solvency status, while Beutler (1985) used a management systems framework in a discussion of the non-technical and philosophical tools essential for financial planners to understand their clients. Danes and Bauer (1987) explored the use of a similar framework in

developing a financial management extension consultant program to help counselors and clients assess, monitor, and resolve financial problems.

Lytton, Garman, and Dail (1987) used a management systems framework for the purpose of developing a descriptive profile of financial management behaviors related to financial competencies. These applications were followed by Titus, Fanslow, and Hira (1989) who applied a management systems model to explain how family financial managers plan and implement resources to meet goals. Churaman (1990) used a management systems type framework in analyzing the process of money management skills by family financial managers, while Williams (1991) used the holistic nature of systems theory to examine household financial management in terms of specific procedures and behaviors.

Another attempt to utilize frameworks requiring inputs, throughputs, and outputs to understand family financial situations included research conducted by Mugenda, Hira, and Fanslow (1990) who used Deacon and Firebaugh's (1988) theory of the family resource management system to assess the causal relationship among communication, money management practices, satisfaction with financial status, and quality of life using 123 personal interviews. Danes, Rettig, and Bauer (1991) also successfully employed a management systems framework to investigate factors that were associated with the family's intention to change its financial situation in the next three years. Danes and Rettig (1993) investigated factors associated with an individual's intentions to change the family financial situation of 337 farm respondents, and Fitzsimmons and Wakita (1993) used 23 different family resource management variables, based on an input, throughput, and output framework, to represent different aspects of family resource management in an attempt to develop a financial management scale. More recently, Lazzarone (1996) used a systems model to examine objective and subjective indicators of satisfaction with finances among 129 rural older adults in a western state. Researchers have reported general success in the application of management systems frameworks in the analysis of family financial management processes.

Explanation and Application of Empirical Model

Leimberg et al.'s (1993) financial management model provided the theoretical framework for this research. Empirically, for the purpose of this research, emphasis was given to the role that gender, age, marital status, occupation, self-employment, income, race, and education play in differentiating among risk attitudes (investor risk tolerance) within the background analysis stage of the framework. The hypothesized classification relationships among gender, age, marital status, occupation, self-employment, income, race, and education to investor risk tolerance are shown in Figure 2.

Once a background analysis is completed by an investment manager, objectives can be established, investment and financial plans developed and executed, and performance measured. Depending on the outcome of an investment management strategy, investment managers can decide to reconsider objectives and revise plans, hold steady until the next measure of performance, or conclude that the financial objective has been attained. The output of this model, attained objectives, can be measured in economic terms by assessing how closely actual investment results match initial objectives, both in terms of desired portfolio risk and return requirements (Sharpe & Winter, 1991).

The empirical model relates to the conceptual framework by clarifying the role played by certain demographics in classifying individuals into investor risk-tolerance categories. The demographics are shown to have a direct classification and differentiation effect on investor risk tolerance. This representation is important, because it indicates that the establishment of objectives and investment plans is not entirely an intuitive mechanism (Sharpe & Winter, 1991), but rather, investment managers do employ both quantitative and qualitative inputs prior to establishing, implementing, and controlling financial and investment planning functions. Furthermore, as shown in the empirical model, the estimation of someone's investor risk tolerance must precede the establishment of objectives and development of plans.

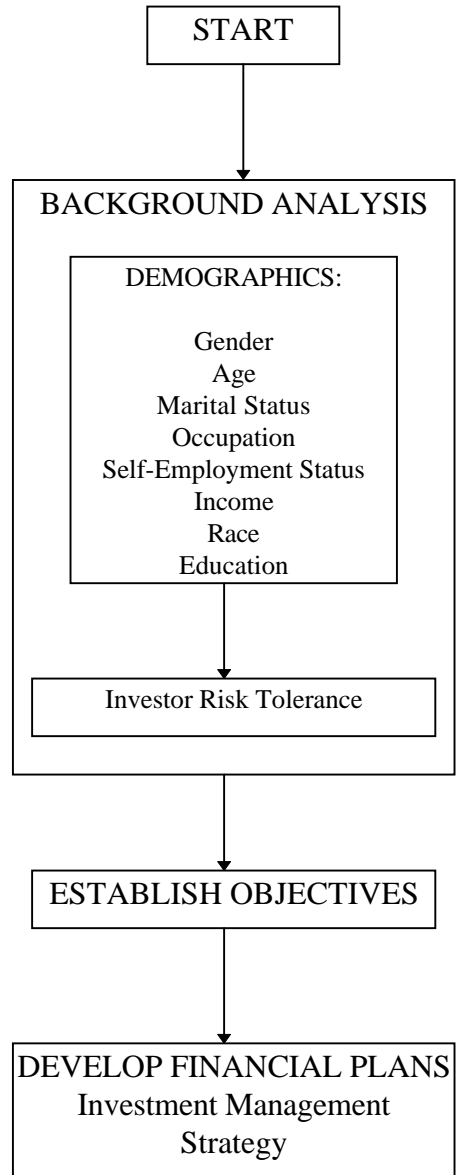


FIGURE 2
Empirical Model

An Empirical Model Indicating the Input Role of Investor Risk Tolerance, as Predicted by Eight Demographic Characteristics, Leading to the Establishment of Objectives and the Development of an Investment Management Strategy.

Definitions

The following definitions were used for the purposes of this study:

Investor Risk Tolerance

In this research, investor risk tolerance (the dependent variable) referred to the maximum amount of investment risk someone was comfortable taking (Schaefer, 1978). Risk tolerance induces an order relation on risk evaluation. Schaefer described the relation this way: “two persons may very well agree on the riskiness of a set of gambles, but may nevertheless prefer different gambles, rank-ordering them differently according to their personal tolerance. This is not to say that people should agree on riskiness of options” (p. 17).

In general, one can expect individuals with low risk tolerance to act differently with regard to risk than individuals with a high risk tolerance. Someone with a high level of risk tolerance would be expected to “accept a higher exposure to risk in the sense of taking sole responsibility, acting with less information, and requiring less control than would” someone with a low level of risk tolerance (MacCrimmon & Wehrung, 1986, p. 34). Individuals with low levels of risk tolerance generally: (a) require lower chances of a loss, (b) choose not to operate in unfamiliar situations, (c) tolerate less uncertainty, and (d) require more information about the performance of an investment (MacCrimmon & Wehrung). In summary, high risk-tolerance individuals accept volatile events, while low risk-tolerance individuals require certainty.

The following demographic definitions are provided in order to clarify why these characteristics continue to be considered by many investment managers and some researchers to be effective in differentiating among levels of investor risk tolerance, and why they were used as components within the background analysis stage in the empirical model.

Gender

Gender (i.e., male or female) was considered an important investor risk-tolerance classification factor because more men than women tend to fit the personality trait called “thrill seeker” or “sensation seeker” (Roszkowski et al., 1993). There also is a “prevalent belief in our culture that men should, and do, take greater risks than women” (Slovic, 1966, p. 169), which has generated a consensus among investment managers that gender is an effective differentiating and classifying factor.

Age

Investment managers use this input as a measure of the time remaining until a client's financial assets are needed to meet goals and objectives. In addition to being used as a proxy for time, investment managers also use age as a measure of someone's ability to recoup financial losses. It is widely assumed that older individuals have less time to recover losses than do younger individuals, and as such, older individuals will have lower risk tolerances.

Marital status

Investment managers consider marital status (i.e., married, never married, divorced, separated, and widowed) an effective factor in distinguishing among levels of investor risk tolerance for two reasons. First, it is assumed that single individuals have less to lose by accepting greater risk compared to married individuals who often have responsibilities for themselves and dependents. Second, it is assumed that married individuals are more susceptible to social risk, which is defined as the potential loss of esteem in the eyes of colleagues and peers, if an investment choice leads to increased risk of loss (Roszkowski et al., 1993).

Occupation

As defined in this research, occupation refers to the principal activity in which someone engages for pay. Examples include the following: manual labor, physician, manager, educator, and administrative personnel. Some investment managers have concluded that higher ranking occupational status (e.g., business executive, attorney, etc.) can be used as a classification factor related to higher levels of investor risk tolerance (Roszkowski et al., 1993).

Self-Employment

Respondents were defined as being self-employed if their incomes came directly from their own business, trade, or profession rather than through salaries or wages from an employer. Investment managers have assumed that self-employment status automatically leads to higher levels of risk-taking, and that, other things being equal, self-employed individuals will typically choose riskier investments and accept increased investment volatility as compared to people who work for others on a straight salary (MacCrimmon & Wehrung, 1986).

Income

According to MacCrimmon and Wehrung (1986), upper income persons (i.e., individuals with incomes greater than \$70,000 per year from all sources and before taxes) and millionaires

(i.e., individuals who derive a portion of their income from assets valued at more than \$1 million) tend to take greater risks than individuals with lower incomes. Investment managers have concluded that increasing income levels are associated with access to more immediate resources (O'Neill, 1996), leading some to conclude that increased levels of income lead to increased levels of risk tolerance.

Race

According to researchers such as Zhong and Xiao (1995) and Sung and Hanna (1996a), different cultural values, preferences, and tastes may affect the risk tolerance of Whites and non-Whites. There is general consensus among personal finance researchers that Whites have higher investor risk tolerances than non-Whites. Reasons for this include: (a) non-Whites may not have the same exposure to banks and other financial institutions as Whites, (b) minority groups may be exposed to non-traditional investment opportunities, (c) many non-White cultures tend to be oriented towards the past or present rather than oriented towards future returns (Zhong & Xiao), and (d) Whites, in general, may possess greater confidence in their analytical and decision making skills (MacCrimmon & Wehrung, 1986).

Education

It is argued by some that increased levels of education (i.e., formal attained academic training) allows someone to assess risk and benefits more carefully than someone with less education. Higher education has been found to encourage risk taking (MacCrimmon & Wehrung, 1986), and as such, investment managers assume that increased levels of education are associated with increased levels of risk tolerance.

Limitations, Assumptions, and Delimitations

Limitations

The data set used in this study was the 1992 Survey of Consumer Finances (SCF). The Survey was sponsored by the Federal Reserve Board in cooperation with the Department of Treasury and was conducted by the National Opinion Research Center at the University of Chicago. The Survey was originally designed as an instrument for the study of household assets and liabilities. While the data set offers researchers a diverse sample, the Survey's measurement of investor risk tolerance relies on one question, namely, "which of the following statements

comes closest to the amount of financial risk that you are willing to take when you save or make an investment?" Respondents were provided four choices ranging from substantial risk, above average risk, average risk, or no risk. Previous risk assessment research suggests that the measurement of risk tolerance via a single question may not adequately measure investor risk tolerance in some circumstances (MacCrimmon & Wehrung, 1986). This limitation in the data set must be acknowledged. However, based on an analysis of response rates to the question, it appeared that the number of respondents per high, average, and no risk-tolerance categories was consistent with response patterns found in previous research (MacCrimmon & Wehrung, 1985), indicating that the item had sufficient face and criterion related validity for use in this study (Hawley & Fujii, 1993-1994; Lee & Hanna, 1995; Sung & Hanna, 1996b).

It is further acknowledged that while the sample used in this research accurately reflects a portion of the investing public, it also is recognized that due to over sampling of high income, primarily White, married, and professionally employed respondents, generalizations can be made only to the sample frame used and to specific groups within the broader population, such as investment management clientele. This limitation indicates the need for further research using different populations and samples that can be used to confirm the results of this examination.

Assumptions

The following specific research assumptions were made as a result of using a pre-existing data set: (a) respondents answered all relevant questions truthfully, (b) all statistical coding and array creation and management conducted at the Federal Reserve was done correctly, (c) the final SCF public use tape correctly reflected respondent answers, and (d) the data were entered and analyzed appropriately and accurately. It also was assumed that investment managers do not assign precise values to investor risk tolerance on a continuum variable. It was determined more likely instead that investor risk tolerance falls within a risk-tolerance category (MacCrimmon & Wehrung, 1986; Roszkowski et al., 1993).

Delimitations

This study was delimited by acknowledging that no attempt was made to test all of the demographics that are used to classify individuals into investor risk-tolerance categories. According to Roszkowski et al. (1993), there are at least 12 demographics that are used to differentiate among levels of investor risk tolerance. However, some of these characteristics are

empirically weak (e.g., birth order), while others are not used consistently by investment managers or researchers (e.g., the assumption that business executives tend to take less risks with their own money than with their firm's funds). Research findings, conclusions, and implications were reported only for the eight most widely used and the most researched demographics that are generally considered to be the most effective investor risk-tolerance differentiating and classifying factors (i.e., gender, age, marital status, occupation, self-employment, income, race, and education).

The following delimitations were applied in this study: (a) due to insufficient response data for certain groups within the sample, the tested variables for marital status and race included some collapsed categories; (b) only respondents who indicated that they were currently working for pay were included in the sample; (c) resulting occupations were classified using 1980 U.S. Census categories; (d) data analysis techniques allowed for only one primary occupational code to be used, thus, a respondent's primary occupation was used as the classification standard; (e) respondents with incomes above \$1 million were deleted from the sample in order to alleviate the negative effects of outliers in the data analysis; (f) the data were not weighted; and (g) data were collected cross-sectionally. This last delimitation is important, as the use of cross-sectional data does not allow for determining if risk tolerance constitutes a fixed personality attribute or whether risk tolerance fluctuates as a result of economic, cultural, or personal changes. Additionally, this study was delimited by the fact that the researcher did not control the sample selection, questions asked, how questions were asked, or response rate adjustments. As such, it is acknowledged that respondents to the SCF do not represent a true random sample, because respondents selected themselves by volunteering and answering questions.

Organization of the Remainder of the Dissertation

This chapter has provided an overview of how investment managers use demographics when differentiating among and classifying individuals into investor risk-tolerance categories. The Leimberg et al. (1993) conceptual framework, and an explanation of demographics commonly thought to be effective in classifying individuals into investor risk-tolerance categories, were presented. The purpose, justification, and specific research question to be answered also were presented. The chapter concluded with definitions, limitations, assumptions, and delimitations.

The remainder of this dissertation is organized as follows: (a) Chapter II - "Review of Relevant Literature," (b) Chapter III - "Methodology," and (c) Chapter IV - "Finding and Results," (d) Chapter V - "Discussion, Conclusions, Recommendations, and Implications," (e) "References," and (f) "Vita."

CHAPTER II

REVIEW OF RELEVANT LITERATURE

The initial literature review for this research project was conducted via an Internet search of 12,500 journals, several hundred dissertation abstracts, and 55 relevant professional publications, including monographs, books, news releases, and subscriptions obtained by the researcher. Key words were used to narrow the search to relevant pieces of literature. Key words and phrases used in the search process included: age, gender, marital status, occupation, wealth, income, success, race, information, education, ethnicity, and number in household in relation to risk. Other key words and phrases included risk tolerance, risk preference, risk aversion, prospect theory,⁸ and psychological aspects of risk. These key words and phrases produced documents, that in turn, provided valuable insights and additional literature resources. The final analysis of relevant literature revealed over 250 pieces of classic, definitive, and influential pieces of literature (determined by a cross-referenced search of research literature in recognized bibliographies and repeated references in the literature). Over 100 research articles were directly applicable to the review of previous research and methodologies.

This review of literature focuses attention on three areas: (a) a historical review, (b) empirical findings from previous research relating to the eight demographics that were analyzed in this study (i.e., risk tolerance in relation to gender, age, marital status, occupation, self-employment, income, race, and education), and (c) a summary of past research findings.

Historical Context

The study of investor risk tolerance is not new. Individual risk tolerance has been of interest to investors and academics for hundreds of years. According to Bernstein (1996), the modern conception of risk “is rooted in the Hindu-Arabic numbering system that reached the

⁸ Prospect Theory is a model of decision making designed to emulate the processes that individuals actually use in decision making. This model describes a general pattern of choice behavior of the average investor where investors evaluate their choices in terms of the potential gains and losses relative to reference points (Statman, 1995). Prospect Theory was developed by Kahneman and Tversky (1979). They termed the phrase “Prospect Theory” in hopes that people would notice and remember their research; the term has little to do with the theory’s underlying hypotheses (Bernstein, 1996).

West seven to eight hundred years ago” (p. 3). Bernstein stated that the “serious study of risk began during the Renaissance, when people broke loose from the constraints of the past and subjected long held beliefs to open challenge” (p. 3). The first serious attempt to measure objective risk arose when Chevalier de Mere, using a question developed by Luca Paccioli (the person who developed double-entry bookkeeping), challenged Blaise Pascal to solve the following puzzle: how does one divide the stakes of an unfinished game of chance between two players when one of them is ahead. Collaborating with Pierre de Fermat, Pascal was able to solve the problem, and in turn, discover the basic laws of probability, or what Bernstein called the mathematical heart of the concept of risk.

The use of probabilities was primarily the domain of gamblers until the early 1700s. By 1725 the English government was using probabilities to determine life expectancies, and private entrepreneurs were using probability techniques to place marine insurance. By 1730 Abraham de Moivre had discovered the concept of standard deviation and the bell curve. Even more important to the subject of risk tolerances was the conceptualization of marginal utility and loss aversion by Daniel Bernoulli in 1738 (Bernstein, 1996). Bernoulli found that the satisfaction resulting from a small increase in wealth was inversely proportionate to the quantity of goods already possessed. Bernoulli concluded that as individuals increased their wealth, they required greater guaranteed returns in order to risk more wealth, and in general, people tended to prefer less risk to more. As Bernstein stated, “Bernoulli’s statement stood as the dominant paradigm of rational behavior for the next 250 years and laid the groundwork for modern principles of investment management” (p. 5).

Risk tolerance research did not re-emerge as a subject of importance until the 1900s, and as Bernstein (1996) pointed out, most research attempts to understand investor risk tolerance have occurred recently. Only a handful of research endeavors to understand risk-taking propensities were conducted prior to the 1950s. Two notable studies prior to the 1950s were undertaken by Keynes (1921) and Knight (1921). Up until this time economists accepted Bernoulli’s logic basis of risk-taking propensity without question. Little additional research was conducted between the Great Depression and the end of World War II, with the notable exception of Keynes’ (1937) publication of *The General Theory*. The lack of risk-tolerance research was primarily due to the fact that economists were preoccupied with social and political problems, and

not interested in advancing research of interest to investors, because it was commonly assumed that the Great Depression was a result of excesses in the investment markets.

It was not until the late 1940s, near the end of World War II, that economists turned their attention to exploring Bernoulli's original logic based explanation of risk-taking propensities. Friedman and Savage (1948) were the first to challenge the standard utility function assumption by showing that most people do not have a constant risk tolerance throughout the entire domain of wealth. Friedman and Savage postulated a utility function with both risk-taking and risk-avoiding segments. Concurrently, the study of risk-taking propensities also was taking place outside the realm of economics. The earliest work on the recognition of risk was concentrated in the area of consumer behavior (MacCrimmon and Wehrung, 1984). Researchers in the fields of finance (e.g., Cohn, Lewellen, Lease, & Schlarbaum, 1975; Markowitz, 1959; Siegel & Hoban, 1982), business (e.g., Fitzpatrick, 1983), natural hazards (e.g., Kunreuther, 1979), and natural situations (e.g., Newman, 1972; Slovic, Fischhoff, & Lichtenstein, 1978) also have given attention to measuring risky situations and surveying perceived individual risks.

During the late 1950s and early 1960s, a major advancement in the study of choice in risky situations was advanced by Wallach and Kogan (1959; 1961). These researchers developed the widely used Choice Dilemmas Questionnaire to measure risk tolerance in everyday life situations. The original questionnaire required that subjects advise other individuals regarding 12 choices with two outcomes: a sure gain or a sure loss. An example of these questions included the following: "Mr. A, an electrical engineer, has the choice of sticking with his present job at a modest, though adequate, salary or of moving on to another job offering more money but no long term security. Please advise Mr. A by deciding what probability of success would be sufficient to warrant choosing the risky alternative" (Wallach & Kogan, 1959, p. 558). These types of choice dilemmas were commonly used to measure risk-taking propensities until the mid-1970s. Behavioral economists and psychologists supported the use of choice dilemmas, while economists advocated the use of utility functions. After the mid-1970s both approaches came under increased attack for lack of validity and reliability due to the one dimensional nature of these types of risk assessments.

The lack of consistency between and among distinctive choice dilemma questionnaires administered by different researchers was revealed as far back as 1962 by Slovic who concluded

that choice dilemma measures lacked sufficient validity and reliability to be of much predictive use. Slovic came to this conclusion after examining all forms of the choice dilemma instrument, including dot estimation tests, word meanings tests for category width, life experiences inventories, multiple choice exams, recreational activity measures, job preference inventories, gambling assessments, and peer ratings. Kogan and Wallach (1964), the creators of the Choice Dilemmas Questionnaire, also found no evidence of general risk propensity across situations. Later researchers concluded that these findings were partially attributable to the one dimensional type questions used in the instruments which required respondents to state how risk averse or tolerant they perceived themselves to be. MacCrimmon and Wehrung (1986) concluded that one dimensional questions (e.g., “how risk tolerant are you?”) measure only a small part of the multidimensional nature of risk, and that most people overestimate their risk preferences when answering these type of questions. MacCrimmon and Wehrung also concluded that “there is no particular reason to believe that a person who takes risks in one area of life is necessarily willing to take risks in all areas” (p. 51).

During the time choice dilemmas were being used extensively, the use of utility functions continued as a favorite method for measuring individual risk tolerances;⁹ however, more recent studies conducted by Kahneman and Tversky (1979) and others (e.g., Bell, 1982; Loomes & Sugden, 1982; Payne, Laughhunn, & Crum, 1984; Shefrin & Statman, 1985, 1993; Tversky & Kahneman, 1981) shed doubt on economists’ claims that risk-taking propensities and preferences could be represented and understood within a utility function environment. Kahneman and Tversky found that “the magnitudes of potential loss and gain amounts, their chances of occurrence, and the exposure to potential loss contribute to the degree of threat (versus opportunity) in a risky situation” (p. 266). Kahneman and Tversky found that people were consistently more willing to take risks when certain losses were anticipated than when certain gains were anticipated. “As the chance, size, or exposure to potential losses (including opportunity costs) increases, the degree of threat increases. Increases in the magnitude, chance,

⁹ The “expected utility of any action is calculated by multiplying the probability of each uncertain event by the utility of the outcome arising from the event and adding up all these mutually exclusive and exhaustive products” (MacCrimmon & Wehrung, 1986, p. 104). In basic terms, a representation is developed from choices having the highest expected utility, where utility is defined as the satisfaction derived through a choice.

or exposure to potential gains increases the ‘opportunity’ aspect” (MacCrimmon & Wehrung, 1986, p. 182). Additional research since the mid-1970s has substantiated the hypothesis that individuals, in general, exhibit risk-taking preferences for losses and risk avoidance preferences for gains (Statman, 1995; Tversky & Kahneman, 1981). These results suggest that reliability problems might be associated with risk-tolerance utility functions, because utility functions tend not to be generalizable when choices are framed both positively and negatively with identical payoff structures. In summary, the use of choice dilemmas and utility functions, as procedures to measure investor risk tolerance, may be inadequate and inappropriate. It has been recommended that, instead of relying on choice dilemmas and utility function, investment managers and researchers should attempt to measure investor risk tolerance in a direct, multidimensional, manner (MacCrimmon & Wehrung, 1986; Okun, 1976; Okun, Stock, & Ceurvorst, 1980; Slovic, 1962; Statman, 1995).

Demographics Related to Risk Tolerance

The empirical study of investor risk tolerance in relation to demographics is limited. Further, according to MacCrimmon and Wehrung (1986), “much of the past research on risk has focused on how people perceive risks as well as rules for choice in risky situations. Little of this work has been concerned with the people who must make risky decisions” (p. 50). Additionally, much of the previous research has tended to use unrealistic settings and events far removed from actual risks faced by investors. Another criticism of previous research (especially experimental studies) is that students, rather than individuals more likely to face actual investment risks, have been used as subjects (Okun, 1976; Okun et al., 1980).

MacCrimmon and Wehrung (1986) provided the seminal literature and research review concerning risk-tolerance studies from the period 1928 through the early 1980s. They found that empirical findings relating to risk tolerance and age, nationality, number of dependents, gender, race, wealth, income, and occupation were contradictory over the four decade span of review. Again, contradictory findings were found to be the result of researchers failing to take into account the multidimensionality of risk and the subjectivity of risk tolerances. Additionally, validity and reliability problems associated with studies using utility theory as a theoretical basis, as explored by Prospect Theory researchers (e.g., Tversky & Kahneman, 1981), placed serious

doubts on the veracity of research findings, conclusions, and implications of work done prior to 1974.

The remainder of this literature review examines research associated with the demographics as outlined in the introduction. Previous research findings are presented in the following order: (a) those research endeavors that found a relationship between demographics and risk tolerance, (b) those that did not find a relationship, and (c) those research studies with inconclusive findings. A brief description of each study's objective and methodology is provided at the first primary point of reference and omitted thereafter in order to reduce redundancy.

Gender and Risk Tolerance

According to Slovic (1966), a “prevalent belief in our culture is that men should, and do, take greater risks than women” (p. 169). This assumption has been confirmed by other researchers (Higbee & Lafferty, 1972). Blume (1978), when reporting the results of a unique national study of New York Stock Exchange (NYSE) investors that employed a combination of descriptive and multivariate statistics, indicated that men who own and invest in equities avoided risk less than women with similar characteristics. This finding was affirmed by Coet and McDermott (1979) who studied the effects of gender, type of instruction, and group composition on general risk-taking behavior using an experimental method with 200 college students, and by Rubin and Paul (1979) who designed an experimental study to examine systematic risk taking by gender over the life cycle as part of a larger model of risk-tolerance behavior. Rubin and Paul found that males consistently demonstrated greater risk-taking behaviors than did females.

The assumption that men generally prefer more risk than women when investing continues to receive credence in publications like *Money*. For example, Belsky, Kobliner, & Walmac (1993) concluded that men and women differ about money and related risk tolerances. Although not grounded in original empirical research, the *Money* article was based on research findings from sociology, psychology, and other social science studies.

During the 1990s researchers continued to conclude that men were more willing to take financial risks than were women. Hawley and Fujii (1993-1994), Sung and Hanna (1996b), and

Xiao and Noring (1994) each used a version of the Survey of Consumer Finances (SCF)¹⁰ to obtain data for regression type analyses (e.g., Ordinary Least Squares, logit, probit, and tobit), where willingness to take financial risks was defined as the dependent variable, and gender (among a number of other variables) was operationalized as an independent variable. These researchers concluded that men were more willing than women to take financial risks. Bajtelsmit and Bernasek (1996), in reporting findings from a survey of literature, concluded that women invest their pensions more conservatively than men, and that, in general, women are less risk tolerant than men. Lytton and Grable (1997) analyzed gender differences in financial attitudes from a random sample of 592 tax payers from a mid-Atlantic state; they found that males expressed more confidence in their financial situation(s) and higher risk-taking propensities in relation to financial management strategies than women.

As indicated above, there is evidence to suggest that a relationship exists between gender and investor risk tolerance, with men tending to take more risks than women. Furthermore, it is commonly accepted that gender can be used effectively to classify individuals into investor risk-tolerance categories; however, researchers have not reached consensus on this point. There are, however, a number of empirical studies which indicate that there are no differences between men and women in relation to risk tolerances.

Blum (1976) used a random sample of 90 male and 91 female professionals and business people, clerical workers, semi-skilled to skilled personnel, housewives, and retired individuals from the New York City area to explore gender differences in risk taking. Blum asked respondents to assume that they had received a sum of money equal to one year's income, with the stipulation that the money must be invested rather than spent, and that they must choose one of four investments. Fourteen judges were used to rank the four investments in terms of riskiness. Based on the judges' estimates, Blum analyzed means and standard deviations of responses. He concluded that the difference between men and women was not statistically significant.

McInish (1982), who conducted a random sample survey of 3,000 investors, arrived at a similar conclusion. McInish measured specific personality characteristics and locus of control in

¹⁰ The Survey of Consumer Finances is a data collection effort with the goal of providing an accurate representation of the distribution of elements composing family balance sheets across families in the United States. The SCF is conducted every three years, and the data are available from the Inter-University Consortium for Political and Social Research and the Federal Reserve Board.

relation to portfolio risk as measured by beta. Using a form of multiple regression, he found that gender was not a significant factor in explaining risk tolerances. Using t-tests, ANOVA, and regression analysis to analyze data from a random sample of 480 investors, Masters (1989) also found no difference in investor risk tolerances by gender.

Schooley and Worden (1996) and Haliassos and Bertaut (1995), using data from the 1989 and 1983 SCF respectively (each employing a form of regression analysis), concluded that gender did not appear to influence stockholding. Furthermore, Fitzsimmons and Wakita (1993) found no difference in male and female family financial managers' expectations of future financial condition using survey data from a random sample of 2,510 household financial managers drawn from rural counties in eight states. Most recently, Palsson (1996) employed a logit regression to determine if risk tolerance varied with household characteristics. She used Swedish cross-sectional data based on 1985 tax returns from more than 7,000 households to conclude that risk tolerance did not systematically change according to gender. Researchers such as Fitzsimmons and Wakita, Haliassos and Bertaut, Masters (1989), McInish (1982), Palsson, and Schooley and Worden offered evidence indicating that a relationship between gender and risk tolerance may be nothing more than myth.

Not all studies have been as conclusive as those just mentioned. Baker and Haslem (1974), using data gathered by means of a mail questionnaire of 851 active customers of five brokerage firms in the Washington, D.C. area, found conflicting gender based results. They concluded that gender plays a significant role in determining an investor's desire for dividend yield and price stability (with women preferring these attributes), but no relationship between gender and expected price appreciation. Bonoma and Schlenker (1978) obtained equally perplexing results from their study. Bonoma and Schlenker constructed a series of experiments where 30 male and 35 female psychology students were instructed on the use of simple subjective probability and utility scales. The students were asked to actively role-play a decision maker in seven general risky situations. Bonoma and Schlenker found that both men and women acted in similar manners when faced with risky choices. Their findings indicated that risk tolerance is not only multidimensional, but may be sub-dimensional as well. Specifically, when investigating investor risk tolerances it was determined that investigators should provide respondents with a multitude of investment situations which require risk-taking choices. Unfortunately, most prior

research has failed to do this (Okun, 1976), and the record has not improved in the 20 years since Okun conducted his research. Thus, while it is commonly accepted that males are more risk tolerant than females, this conclusion is not a consensus view held by researchers.

Age and Risk Tolerance

Wallach and Kogan (1961) are generally considered to be the first researchers to study the relationship between risk tolerance and age. Their early experimental research used choice dilemmas which indicated that older individuals were less risk tolerant than younger individuals. This finding was responsible for creating an increased research interest on this topic which led to a multitude of other research projects.

In 1966 Botwinick investigated cautiousness in relation to age, sex, and education in the context of 24 “life situations” (including several ‘investing’ type questions) using Wallach and Kogan’s (1961) experimental choice-dilemma test as a basis of investigation. Based on experiments with 90 volunteer older adults and 111 young adults enrolled in psychology courses at Duke University, he found that older subjects were more cautious in their decisions than younger adult subjects. Wallach and Kogan’s choice dilemma test has been the subject of numerous other investigations. For example, Vroom and Pahl (1971) administered a choice dilemmas test to 1,484 managers from over 200 companies, and concluded that older subjects showed a significant negative relationship to risk taking and the value placed upon risk.

During the early 1970s researchers turned their attention from testing the relationship between age and risk tolerance away from choice dilemmas to survey methods, other experimental designs, and objective measures (i.e., deducing risk tolerance from assets owned by individuals). Bossons (1973) used estimates based on data collected in the 1963 SCF to conclude that younger individuals were more risk tolerant than older persons. In 1974, Lease, Lewellen, and Schlarbaum used results from a survey of brokerage firm clientele ($N = 1,000$) and also concluded that age was inversely related to risk tolerance. Okun and DiVesta (1976) obtained similar results from an experiment utilizing 48 younger and older males who were asked to participate in a vocabulary task involving varying degrees of risk under neutral, supportive, and challenging instructions. During this time other researchers, using both survey sampling methods and experimental designs, observed that older adults were more cautious than younger adults (Baker & Haslem, 1974).

The use of more sophisticated statistical methods and a renewed research interest in life-cycle analysis marked a changing point in age/risk-tolerance research in the 1980s. McInish (1982), using data from a random sample of 3,000 investors, found (using regression analysis) significant negative age coefficients in his analysis of personality characteristics and risk tolerances. Morin and Suarez (1983), using data from the 1970 SCF for Canada, attempted to add empirical evidence to the effect of wealth on risk aversion through the life cycle by concluding that risk tolerance decreases uniformly with age.

Risk-tolerance researchers continued to explore age relationships using survey methods, life-cycle effects, and objective measures in the 1990s. Researchers such as Brown (1990), using economic theoretical modeling with macroeconomic data such as Treasury Bill rates, stock and bond market variances, and state contingent values, found that portfolio composition tended to be age dependent. Dahlback (1991), using cross-sectional data from a survey of 443 unmarried Swedish citizens between 22 and 64 years of age, employed bivariate correlation analysis to determine that older individuals were more likely to avoid risk than younger persons.

Similar results were obtained by Hawley and Fujii (1993-1994) and Bakshi and Chen (1994). Bakshi and Chen used a Euler equation utilizing historical time-series data (e.g., stock market prices, price deflators, etc.) from the period 1926-1990 to conclude that a rise in average age was found to predict a rise in investment risk premiums, while Sung and Hanna (1996a), using data from both the 1983 and 1986 SCF to conduct an ordered probit analysis using willingness to take financial risks as the dependent variable, concluded that older individuals were less risk tolerant than younger persons. More recently Palsson (1996), using survey data from 7,000 Swedish households, also concluded that decreasing risk tolerance was correlated with increasing age. The reporting and acceptance of these findings has become so widespread that that there is now substantial consensus among financial advisors that as one ages, the cash portion (i.e., a risk-free asset) of one's portfolio should be increased (Reichenstein, 1996). The trade press has even advocated using age based formulas to create simple investment management strategies to account for the perceived negative relationship between age and risk tolerance (Bengen, 1996; Gitter, 1995; Kapiloff, 1994).

According to Botwinick (1984), "there is a persistent belief that increasing age makes for increasing cautiousness or conservatism. There are research data in support of this belief, but

there are also data indicating otherwise” (p. 166). Okun (1976) concluded that “adult age differences were observed ... only in the case when adults were permitted to refrain from responding to situations depicted ...” (p. 220). Blum (1976) suggested that “variables other than age are more significantly related to a desire for security in decisions concerning investment preferences” (p. 87). For example, based on results from an experiment with 18 younger and 18 older adults using a vocabulary task which involved degrees of risk with a payoff structure that varied either directly or inversely with risk, Okun and Elias (1977) concluded that risk taking was a function of payoff structure, not age.

Recent studies have shed doubts on the validity of claims that age is effective in differentiating between levels of investor risk tolerance. Using a combination of econometric modeling and data from the 1983 SCF, Haliassos and Bertaut (1995) suggested that individuals routinely depart from expected utility maximization, and that other factors, such as education and race account for risk tolerances more than age. Gehrels (1991), using German microcensus data, also found no relationship between age and risk tolerance in his analysis of the life-cycle hypothesis. Lee and Hanna (1991), in attempting to investigate the rate of stock ownership among U.S. households, using log-linear methods to analyze the 1983 SCF, concluded that age was not a significant variable in determining ownership of risky assets.

One of the most significant research studies to understand financial risk tolerance undertaken in recent years was conducted by the Boettner Institute under the leadership of Neal Cutler (1995). Cutler and his associates attempted to explore the concept that “risk-tolerance is a simple one-dimensional attitude” (p. 33) by testing data from a comprehensive mail survey (N = 801). Cutler concluded that there was no cause and effect linkage between age and comfort with financial risk. According to Cutler, “it is a myth to believe that age has an across-the-board effect on financial attitudes” (p. 37).

Research concerning the relationship between age and risk tolerance is not entirely conclusive. Riley and Chow (1992), using an ordinary least squares regression model employing data obtained from 17,697 participants of the Survey of Income and Program Participation, found that relative risk aversion decreased as one aged until age 65, when risk aversion began to increase. Similar results have been obtained by other researchers employing a variety of methodologies. Feldstein and Washburn (1980) used Kogan and Wallach’s (1964) choice

dilemmas questionnaire twice, with an intervening group discussion with 192 volunteer subjects (88 males and 104 females), at 3 age levels. Feldstein and Washburn found that overall, younger subjects preferred more risk than older subjects, but that all age levels shifted their risk tolerance following group discussions. The results of a regression analysis using data from 587 observations of the fraction of total assets invested in risky assets, and the betas of portfolios held with an investment firm, led Holland (1991) to conclude that any differences in the degree of risk tolerance between younger households relative to older households was minimal.

Hutchison and Clemens (1980) used a modified version of the choice dilemmas questionnaire with a 152 participants who ranged in age from 60 to 84. Based on results from a three-factor analysis of variance, Hutchison and Clemens concluded that age effects found in previous studies of young subjects were not present in their study. Schoemaker (1980) used 82 MBA students, who were taking an introductory quantitative methods course at the Wharton School, as subjects in a two-phase risk-tolerance experiment that focused on general probabilities and risk taking. He found that expected utility theory did not predict better than chance, and that findings of age differences in relation to risk tolerances were inconclusive. Finally, Weagley and Gannon (1991) reported the results of a multinomial logit model from a sample of 249 randomly selected Missouri households. They concluded that as individuals age they take on increasing levels of risk but at a decreasing rate to a point where they begin to reduce the risk in their portfolio. The relationship between age and investor risk tolerance was not linear. Financial planners have begun to acknowledge this type of finding in practice. While there may be some differences between age groups, some investment managers do acknowledge that age/risk-tolerance assumptions simply may not be correct (Gibson, 1997).

Recent research indicates that past conclusions on aging and cautiousness have been plagued by critical problems which lead to contradictory results. Okun (1976) outlined three problems associated with early research attempts: (a) prior to 1976 only one study included young, middle-aged, and older adults; (b) all investigators working in this area employed cross-sectional analyses; and (c) most studies were not multidimensional in design, indicating a lack of theoretical grounding. In general, adult age differences were observed only in those cases when adults were permitted to refrain from responding to situations presented to them; when

respondents were not allowed to refrain from responding, no adult age differences were found (Okun).

Okun, Stock, and Ceurvorst (1980) determined that much of the past research also was plagued by researchers drawing samples from extremes of the adult age range, relying on single criterion variables, and not reporting data bearing on the reliability and validity of their measures. Okun et al. concluded that “the currently popular notion that people become more cautious as they grow older” was inaccurate (p. 463).

Although an inverse or negative causal relationship between age and investor risk tolerance has long been accepted, based on research analysis conducted by investigators like Okun et al. (1976, 1977, 1980), future research attempts must take into account past methodological problems that appear to diminish any causal effects. Regardless of Okun et al.’s assertion, due to the number of investment managers using age as an investor risk tolerance differentiating and classifying factor, researchers should assume such an association exists when developing hypotheses (Sung & Hanna, 1996a).

Marital Status and Risk Tolerance

According to Baker and Haslem (1974), “the balancing of risk and return represents the classic dilemma faced by investors” (p. 469). It is widely assumed by investment managers that marital status is a factor that significantly influences risk and return preferences, and an individual’s satisfaction with finances (Lazzarone, 1996). In some circumstances researchers have found that non-married individuals prefer more investment risk than similar married individuals.

Sung and Hanna (1996a, 1996b) concluded that single females were less likely to take financial risks than single males and married individuals. Lee and Hanna (1991) found a positive relationship between stock ownership, wealth levels, and being a married couple. At a given level of wealth, single-headed households tended to have more stock ownership than married couple households. Lee and Hanna went on to state, “this result could be interpreted as being due to single-headed households having less risk aversion than married couple households” (p.137).

Although widely accepted as true, very little evidence exists to substantiate the claim that “unmarried individuals are more prone to take risks than married individuals” (Roszkowski et al., 1993, p. 220). Researchers have suggested that married individuals, not singles, possess greater risk-taking propensities, although others have failed to find any statistically significant relationship

between marital status and risk tolerance (Haliassos & Bertaut, 1995; McInish, 1982). Masters (1989), who administered Wallach and Kogan's (1961) choice dilemmas questionnaire to 480 randomly sampled investors from a midwestern investment firm, reported that singles appeared to be more conservative investors than marrieds; however he was unable to offer an explanation to explain this finding. Mugenda, Hira, and Fanslow (1991) interviewed 123 randomly selected family financial managers from a midwestern town. They concluded, using path analysis, that marital status was positively related to satisfaction with quality of life and higher levels of wealth. Hawley and Fujii (1993-1994) concluded that among females, married women were the least risk averse, and that male heads of household (i.e., single) did not differ from married men in their risk tolerances.

Findings relating to marital status and risk tolerance tend to be conflicting. For example, Lee and Hanna (1995), in an apparent reversal of earlier findings based on an analysis of the 1983 SCF, suggested that single males and married respondents had significantly higher predicted probabilities of being willing to take risks than single females. Similar confusing findings have been presented by Baker and Haslem (1974) who used a sample of 1,623 active investors, and Xiao and Noring (1994) who analyzed data from the 1986 SCF. Others, such as Lazzarone (1996) who analyzed data collected from 129 older subjects who were surveyed regarding satisfaction with finances, have concluded that marital status was not a significant classification factor for either marrieds or singles. In general, conclusions from the literature make it difficult to confidently hypothesize about the expected relationship between marital status and risk tolerance; however, as pointed out above, it is still widely accepted among investment managers that single individuals are more risk tolerant when compared to married persons (Roszkowski et al., 1993).

Occupation, Self-Employment, and Risk Tolerance

According to Roszkowski et al. (1993), other things being equal, different occupations can be used to differentiate between levels of investor risk tolerances. For example, it has long been believed that self-employed individuals, salespersons, and people employed by private firms rather than public employers tend to be more risk tolerant (both generally and in relation to investments) (Leonard, 1995).

An early attempt to test occupational and employment status relationships on risk tolerances was undertaken by Meyer, Walker, and Litwin (1961). Meyer et al. used a risk-

tolerance questionnaire similar to the choice dilemmas questionnaire in an experiment utilizing 31 managers and 31 entrepreneurs. They found that entrepreneurial types showed greater tolerance for intermediate level risks than comparable nonentrepreneurial subjects. Similar findings were obtained by Grey and Gordon (1978), who followed the career paths of 700 persons in one large multinational company. Grey and Gordon related the number of promotions people received to scores on a risk-taking scale. They found that risk takers, when measured in a multidimensional manner, tended to be promoted more rapidly than those who scored lower in risk taking. This finding was similar to one obtained by Hammond, Houston, and Melander (1967) who regressed data from occupation scales in the 1953 and 1962 SCF to determine which factors influenced life insurance premium expenditures. Hammond and his associates concluded that entrepreneurial types showed tolerances for greater risks. Based on an analysis of the responses to a series of investor risk-tolerance questions by 1,015 randomly chosen investors (author's note: the original study was undertaken by the Wharton Survey Institute in 1974), Blume (1978) concluded that "professionals in particular and the self-employed had a lower propensity to minimize risks than did other investors and were at least as willing as the rest of the stockholding population to assume substantial risks. Corporate officials, on the other hand, were the least willing of all occupational groups to assume substantial risks" (p. 124).

Quattlebaum (1988) explained this phenomenon in terms of "symptoms of timidity" (p. 68). He concluded, based on an analysis of proprietary client data obtained from Brown Brothers Harriman, Inc. of New York City, that occupations such as non-surgical physicians, non-surgical dentists, and not self-employed lawyers represented positions of timidity. Aggressive occupations included entrepreneurs, surgeons, independent CPAs, and independent lawyers. Based on Quattlebaum's findings, it appears that individuals who take less risks typically choose occupations with relatively small economic and political risks (Barnewall, 1988). Masters (1989) also found patterns of risk tolerance tied to occupational choice. He found that nonprofessionals (clerical workers, farmers, unskilled and skilled laborers) tended to be more conservative in investment decisions than professionals (educators, doctors, lawyers, business owners, and managers) and retired persons. As Masters pointed out, "this does not mean that they [nonprofessionals] have any less money to invest but, as a group, they probably will invest differently" (p. 154).

Similar results indicating the classification nature of occupational choice on risk tolerances also have been obtained by Haliassos and Bertaut (1995), Lee and Hanna (1995), and Sung and Hanna (1996a, 1996b) each of whom analyzed data from the SCF. These researchers found that persons employed in occupations like farming, business ownership, and managerial positions were more willing to take risks (including financial and investment risks) than those in “low risk” occupations.

Since the early 1970s, only one research team reported conflicting results. Baker and Haslem (1974), using chi-square analysis of independence on data obtained from a random sample of investors ($N = 851$), noted that occupation was not significantly related to risk and return variables. They admitted that their findings were inconsistent with the literature.

Based on the review of relevant occupational/risk-tolerance research, a relationship appears to exist indicating that certain occupations and employment classifications can be said to appeal to individuals with higher risk tolerances, while other occupations and employment classifications appeal to persons with lower overall risk tolerances. Using Masters’ (1989) findings as a guide, nonprofessional occupations (e.g., clerical workers and unskilled/skilled laborers) tend to be associated with lower risk tolerances, while professional occupations (educators, doctors, lawyers, business owners, and managers) appear to be associated with greater risk tolerance.

Income and Risk Tolerance

In 1976, Blume conducted a thorough examination of risk-taking behavior, using a combination of data obtained from a large random sample of investors ($N = 1,015$) and an exhaustive research review, and concluded that stockholders with annual gross incomes of \$50,000 or more were willing to take more investment risks than those with lower incomes. Over the years this pattern has been observed frequently, and increased levels of income have become a commonly accepted characteristic of high risk-tolerance persons. Cohn et al. (1975) used a 100 item questionnaire to elicit responses from 972 randomly selected, geographically stratified, brokerage firm clients regarding investment decision processes, goals, asset holdings, and market beliefs. Based on a combination of regression analysis, multiple discriminant analysis, and chi-square analysis, Cohn et al. concluded that relative investor risk tolerance increases with wealth and income. Similar findings were reported by Friedman (1974) who used econometric modeling

techniques to analyze aggregate U.S. employer provided insurance premiums and coverage ratio data. He concluded that higher salaried employees displayed a higher degree of risk tolerance. Schooley and Worden (1996) arrived at the same conclusion based on a multivariate regression analysis of multiple imputed data from the 1989 SCF.

Most recently Shaw (1996), using regression techniques to analyze data from the 1983 SCF, concluded that wage growth was positively correlated with tolerances for risk taking. Based on a random sample of 25,009 observations of residential customer billings in the Mountain Bell Colorado service area, Cicchetti and Dubin (1994) also determined that risk tolerance varied systematically with levels of income. Other researchers using similar methods, primarily analysis of data from the SCF, have arrived at comparable conclusions (e.g., Hawley & Fujii, 1993-1994; Lee & Hanna, 1991; Xiao & Noring, 1994; Riley & Chow, 1992).

The effect of income on risk tolerance is not conclusive however. In 1969, Samuelson used a Bernoulli type utility model to analyze the relationship between affluence and risk tolerance, and income and risk tolerance. He arrived at the conclusion that high salaries were not predictive of greater risk taking or tolerance. Samuelson also added that he failed to find more affluence associated with higher risk tolerance. Blume and Friend (1975) also concluded that risk tolerance remained relatively constant as wealth and income increased. Blume and Friend based their conclusion on a regression analysis of a random sample of 17,056 individual federal income tax returns from the year 1971, and a similar analysis of the 1962 SCF (see also Friend & Blume, 1975). Schoemaker (1980), using experimental methods, also failed to find a relationship between income and risk tolerance. Finally, Palsson (1996) used regression analysis to calculate the degree of risk aversion among households in order to investigate the extent of risk that varied with household characteristics. Based on an analysis of Swedish tax data, Palsson concluded that risk tolerance did not systematically vary with changes in income.

The results of these studies, both pro and con, suggest that caution be used when developing hypotheses concerning income as a differentiating and classifying factor in determining levels of investor risk tolerance. However, based on the empirical evidence offered, a hypothesis suggesting that income is positively associated with investor risk tolerance seems appropriate.

Race and Risk Tolerance

There are few empirical studies concerning the relationship between race and investor risk tolerance. Lefcourt (1965) was the first researcher to explore risk-taking differences between Black and White adults. Using a risk-taking experiment using 30 Blacks and 30 Whites, Lefcourt concluded that Blacks choose fewer low probability bets, made less shifts of bets, and generally took less risks than Whites.

Recently there has been a renewed focus on the relationship between risk-taking propensities and race. Haliassos and Bertaut (1995), Hawley and Fujii (1993-1994), Lee and Hanna (1995), and Sung and Hanna (1996a) each used the 1983 and 1986 Surveys of Consumer Finance to conduct logit and probit analyses of multistage area-probability samples (N = 3,824). Each of these research teams found that White respondents had a higher probability of taking investment risks. Zhong and Xiao (1995) used the 1989 Survey of Consumer Finances to conduct a tobit analysis that showed bonds and stocks were more likely to be held by Whites than non-Whites, controlling for other factors. Zhong and Xiao concluded that since most non-White cultures tend to focus on the past or present rather than the future, non-Whites may not be encouraged to invest in more risky investments which require a relatively long period in order to even out the volatility associated with stock and bond investments. These assertions were confirmed by Sung and Hanna (1996b) who conducted a logistic regression using the 1992 SCF.

Only one study was found to indicate that non-Whites take more risks than Whites. Leigh (1986), using a combination of correlation techniques and econometric models, concluded that non-Whites were more likely to prefer more risk than Whites.

Investment managers and researchers generally accept the notion that there is a relationship between race and investor risk tolerance. Controlling for other factors, Whites are considered to have higher risk tolerances than non-Whites. This difference may be attributable to cultural values, preferences, and tastes. According to Zhong and Xiao (1995) “further investigation will be helpful to enhance the understanding of the investment behavior between Whites and non-Whites” (p. 113).

Education and Risk Tolerance

Education, as used in investor risk-tolerance research, has been defined as the level of formal education completed by an individual (Masters, 1989). Numerous researchers have

concluded that greater levels of attained education are associated with increased risk tolerance. Baker and Haslem (1974), using data from 851 respondents to a risk-tolerance questionnaire that was randomly distributed to customers of five brokerage firms, determined that investors with less education found price stability more important than those with at least some college training. Baker and Haslem acknowledged that their findings conflicted with findings from other researchers that suggested that those with little education were desirous of quick profits from risky trading (Potter, 1971). Hammond et al. (1967) used a general regression model to consider life insurance premium expenditures by household. They found that education of the head of the household was significantly related to premium expenditures, and that those with lower levels of education tended to have lower risk tolerances. Masters (1989) concluded that general education level was not always a factor influencing investment decisions, but that in general, investors with higher education levels tended to invest in higher risk investments. Finally, Shaw (1996) used data from the 1983 SCF to estimate a wage growth equation. She determined that more educated individuals were more likely to be risk takers, and that risk taking explained a portion of the returns to education.

Haliassos and Bertaut (1995) determined that education was an important factor in overcoming the barriers to stockholding, which included an initial risk of loss associated with equities. They also found that those who have not attended college were significantly less likely to hold stocks than those with at least a college degree. Zhong and Xiao (1995), after conducting a tobit analysis using data from the 1989 SCF, reported that increased ownership of bonds and stocks (risky assets) increased with education. Lee and Hanna (1995), who also used data from the SCF, concluded that the proportion of individuals willing to take risks increased significantly with education, while Sung and Hanna (1996a, 1996b), using data from the SCF, also determined that education was statistically significant in determining someone's willingness to assume greater risk.

Although it is generally accepted by investment managers and researchers that increased educational levels are associated with increased levels of investor risk tolerance, there is research to suggest otherwise. Blume (1978), using results from a large random national survey of NYSE investors, concluded that educated heads of households were somewhat less willing than others to take substantial risks, "but at the same time, they reported a less than average propensity for

reducing financial risks to the barest minimum, preferring some intermediate trade-off between risk and expected return” (p. 124). McInish (1982), as a result of a regression of betas against Rotter scores and demographic variables, found that educational levels showed a predicted positive relationship with risk tolerance, but that education coefficients were not significant in any of the regressions.

The literature suggests that a positive relationship between attained education and increased investor risk tolerance is reasonable. However, as with the implications derived from research concerning other demographics, this relationship is not definite, and additional research is warranted.

Research Summary

There is still a persistent belief among investment managers and researchers that (a) men are more risk tolerant than women, (b) older individuals are less risk tolerant than younger people, (c) single individuals are more risk tolerant than marrieds, (d) certain occupations are associated with increased and decreased levels of risk tolerance, (e) individuals with greater income have greater risk tolerances than lower income earners, (f) non-Whites tend to be less risk tolerant than do Whites, and (g) greater educational attainment is associated with increased risk tolerance.

Table 1 provides a summary of the assumed relationships between risk tolerance and demographics. Investigators know that “there are research data in support of these beliefs, but there are also data indicating otherwise” (Botwinick, 1984, p. 166).

Table 1

Summary of Assumed Relationships Between Risk Tolerance and Demographics

Characteristic	Low Risk Tolerance	High Risk Tolerance
Gender	Female	Male
Age	Older	Younger
Marital Status	Married	Single
Occupation	Clerical Workers and Laborers	Professionals
Self-Employment	Non-Self-Employed	Self-Employed
Income	Low	High
Race	Non-Whites	Whites
Education	Less	More

It is important to remember that the eight demographics (i.e., gender, age, marital status, income, occupation, self-employment, race, and education), as differentiating and classifying

factors of investor risk tolerance, have not undergone enough rigorous testing (Sung & Hanna, 1996b). In fact, there is general consensus among researchers (e.g., Blum, 1976; Botwinick, 1984; Okun, 1976; Okun et al., 1980) that studies conducted prior to the mid-1970s tend to have methodological problems which make the validity and reliability of past findings and conclusions doubtful. Specific problems include: (a) samples drawn from extremes of the population, (b) the lack of multidimensional risk-tolerance measures, (c) paucity of data on the scales and indices used, (d) lack of validity involved with objective measures of risk tolerance, and (e) researchers failing to distinguish between and among demographic variables (Okun et al., 1980). As Cutler (1995) suggested, many of the characteristics used to classify individuals into investor risk-tolerance categories may be little more than myth. Samuelson (1989) called some heuristics associated with these demographics “folk wisdom” (p. 32), and stated that folk wisdom is not up to explaining many investor risk-tolerance behaviors. Additional research is needed.

Summary and Analysis

In summary, the review of research indicated that the following relationships regarding demographic characteristics and risk tolerance have support in the literature and in application by investment managers:

- (a) males are more risk tolerant than females,
- (b) younger individuals are more risk tolerant than older individuals,
- (c) single individuals are more risk tolerant than married individuals,
- (d) individuals employed in professional occupations are more risk tolerant than those employed in non-professional occupations,
- (e) self-employed individuals are more risk tolerant than those employed by others,
- (f) high income earners are more risk tolerant than lower income earners,
- (g) Whites are more risk tolerant than non-Whites, and
- (h) individuals with higher attained educational levels are more risk tolerant than those with lower levels of attained education.

This chapter briefly reviewed the history of investor risk-tolerance inquiry. The chapter also detailed previous research which was designed to measure relationships between and among investor risk tolerance and gender, age, marital status, occupation, self-employment, income, race,

and education. This review suggested that while these demographics are widely considered to be effective in differentiating among levels of investor risk tolerance, there is reason to doubt the efficacy of these demographics as discriminating factors. The chapter ended with the conclusion that additional multivariate analysis is warranted. The remainder of the dissertation details the methodology, analysis, findings, conclusions, recommendations, and implications involved in examining the hypotheses listed above.

CHAPTER III METHODOLOGY

Chapter II provided a review of relevant literature concerning the associations among the demographics being tested in this study and investor risk tolerance. The review indicated that gender, age, marital status, occupation, self-employment, income, race, and education continue to be used by investment managers to differentiate among and classify individuals into investor risk-tolerance categories. The review also indicated that consensus among researchers regarding the efficacy of these demographics as differentiating and classifying factors was lacking.

The need for additional empirical testing of the relationships between the demographics of interest in this study (i.e., gender, age, marital status, occupation, self-employment, income, race, and education) and investor risk tolerance is evidenced by four factors: (a) investment managers continue to use demographics to differentiate among and classify individuals into high, average, and no risk-tolerance categories; (b) it is reasonable to assume that investment managers will continue to use these characteristics in the future; (c) although widely used, the application of these demographics in differentiating among levels of risk tolerance has not improved investment performance; and (d) academic findings in relation to risk tolerance and these demographics have been inconclusive and often conflicting.

The purpose of this study was to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. The findings from this research will enhance the ongoing discussion concerning the use of demographics as investor risk-tolerance classification factors, and provide investment managers with an estimate of which demographics are statistically significant for use in assessing clientele risk tolerances during the input phase of the investment management planning process.

The objective of this chapter is to explain the design and methodological procedures that were used in this study. Specific objectives are as follows:

- (a) discuss the survey instrument,
- (b) discuss the sample,

- (c) provide a list of variables with operational definitions,
- (d) present the research question and appropriate research propositions in null form, and
- (e) describe the method of data analysis.

Survey Instrument

The 1992 Survey of Consumer Finances (SCF) was used as the data set for this study. The SCF is a triennial survey designed primarily as an instrument for the study of U.S. household income, assets, liabilities, and demographics (Sung & Hanna, 1996b). The SCF was sponsored by the Federal Reserve Board in cooperation with the Department of the Treasury and conducted by the National Opinion Research Center (NORC) at the University of Chicago.

According to Kennickell, McManus, and Woodburn (1996), the SCF questionnaire took on average, about 75 minutes to complete, though the time required may be as much as three hours for households with very complex finances. The most detailed data are collected on assets (including checking, money market, and savings accounts, IRAs and Keogh accounts, savings bonds, other types of bonds, mutual funds, publicly-traded stocks, trust accounts, annuities, businesses, the principal residence, other real estate, loans made to others, and other assets) and liabilities (including credit card debt, principal residence mortgage debt, other mortgage debt, lines of credit, automobile loans, education loans, other installment loans, loans against stocks and insurance policies, and other loans). Information is also collected on employment history, pension rights, inheritances, marital history, attitudes, and numerous other items (p. 2).

Sample

The SCF was intended to provide an accurate representation of the distribution of many financial variables across the U.S. population. The unit of analysis used in the SCF was the household, and most information was collected from the household's primary economic unit. The primary economic unit was defined as the economically dominant person or couple within a

household together with all persons financially dependent on that person or couple. For the sub-sample used in this study, the primary economic unit was defined as the selected taxpayer together with the spouse and all persons who were financially dependent on that unit.

Sampling data were obtained from an area-probability sample in a multi-stage design constructed from 1980 Census records. The response rate, while not officially reported, has been estimated to be approximately 30%. According to Kennickell et al. (1996),

at the first stage of selection, NORC divided the entire U.S. into geographic units and placed these units into strata based on degree of urbanization, population size, and location. Sixteen large metropolitan areas such as New York, Los Angeles, and other such cities were selected as primary sampling units with probability one. Another 68 primary sampling units were selected at random from the remaining strata. Segments within these primary sampling units were selected with probability proportional to a size measure determined from the 1980 Census population figures. Dwelling units were listed by field staff for each segment, and sample units were selected with probability inversely proportional to the number of housing units listed. Every unit in this part of the sample had an equal probability of selection (p. 2).

The final public use version of the 1992 SCF consisted of 19,530 cases. However, this number was five times the actual amount of useable responses. This overstatement of cases was the result of a multiple imputation technique used by the Federal Reserve to adjust data for missing information. Thus, in reality, the useable data set consisted of five separate replicates each consisting of 3,906 cases. The first replicate contained actual respondent answers, while replicates 2 through 5 contained responses with imputed values.¹¹

¹¹ See Montalto and Sung (1996) for a description of the multiple imputation technique and resulting replicates.

The first replicate was used in this research.¹² The use of the first replicate has precedence in the literature. To date, the majority of researchers using the 1992 SCF have also used the first replicate (e.g., DeVaney, 1995a, 1995b; Hong & Swanson, 1995; Kao, 1994; Malroux & Xiao, 1995a, 1995b; McGurr, 1995; Xiao, 1995; Zhong & Xiao, 1995).

For the purposes of this research, only those respondents who provided useable information concerning gender, age, marital status, occupation, self-employment, income, race, education, and risk tolerance, and who were currently working for pay, were included for analysis. Respondents with incomes above \$1 million were eliminated from the sample as a way to reduce the effect of outliers on the data analysis. These delimitations resulted in a useable sample of 2,626 respondents.

Variable Selection and Data Coding

Dependent Variable

The dependent variable was operationalized as respondent answers to the following risk assessment question in the SCF:

“Which of the following statements on this page comes closest to the amount of financial risk that you are willing to take when you save or make investments?”

The possible responses were as follows:

1. Take substantial financial risks expecting to earn substantial returns
2. Take above average financial risks expecting to earn above average returns
3. Take average financial risks expecting to earn average returns
4. Not willing to take any financial risks

The total SCF distribution of responses to the risk assessment item was 3.70%, 14.60%, 42.10%, and 39.60%, respectively. Responses to the substantial risk category were insufficient to be used appropriately in this multivariate analysis using multiple levels within the eight independent variable categories. Therefore, the substantial and above average risk categories were combined into a single category, consisting of 18.30% of sample respondents. The final

¹² The repeated-imputation inference technique recommended by Montalto and Sung (1996) to utilize all five replicates could not be applied in this analysis because the technique requires a coefficient vector and a variance-covariance matrix for each imputation. The method of analysis used in this study, as calculated with SAS (i.e., canonical discriminant analysis), does not provide either matrix.

dependent variable was comprised of three categories: (a) high risk tolerance, (b) average risk tolerance, and (c) no risk tolerance.

Independent Variables

The following discussion describes the rationale for selecting the eight independent variables included in the empirical model and how they were coded for analysis. A summary of the operationalized variable definitions is provided in Table 2.

Gender. Gender, a categorical variable, was dummy coded (1 = male, 0 = female) to allow its use as an interval level variable. Coding matched the sex reported by each respondent. Gender was included as an independent variable, because gender has been found to be an important investor risk-tolerance classification factor, with more men than women tending to fit the personality trait called “thrill seeker” or “sensation seeker” (Roszkowski et al., 1993). The fact that a “prevalent belief in our culture that men should, and do, take greater risks than women” (Slovic, 1966, p. 169), also prompted the use of gender as an independent variable.

Age. Age, a continuous variable, was coded according to internal SCF calculations based on each respondent’s birth date. Age was selected as an independent variable because investment managers use this input as a measure of the time remaining until financial assets are needed to meet goals and objectives. In addition to being used as a proxy for time, investment managers have also used age as a measure of someone’s ability to recoup financial losses. It is widely assumed that older individuals have less time to recover losses than do younger individuals, and as such, older individuals will have a lower risk tolerance.

Marital status. This nominal level independent variable was dummy coded for use as an interval level variable. There were insufficient numbers of separated, divorced, widowed, living with partner, and other respondents to use these categories separately within a multivariate analysis. Therefore, marital status categories were collapsed and recoded. Married respondents were collapsed with respondents who indicated living with a partner. Respondents who indicated being separated, divorced, widowed, or other were collapsed into a new category called “single but previously married.” Respondents who were never married remained a separate category.

The new categories of marital status were dummy coded as follows: 1 = married (including living with a partner) and 0 = not married; 1 = single but previously married (including

separated, divorced, widowed, and other) and 0 = not single but previously married; and 1 = never married and 0 = other than never married.

Marital status was included as an independent variable because of the general consensus among investment managers that marital status can be used to differentiate among levels of investor risk tolerance. It is assumed that never married individuals and some single but previously married have less to lose by accepting greater risk compared to married individuals who often have responsibilities for themselves as well as dependents. Married individuals are considered more susceptible to social risk, which is defined as the potential loss of esteem in the eyes of colleagues and peers if an investment choice leads to increased risk of loss (Roszkowski et al., 1993).

Occupation. Respondents to the 1992 SCF were asked about their current job status, and whether they were currently working for pay, temporarily laid off, unemployed, disabled, retired, a student, a homemaker, or working in some other type of employment. Responses were sorted and coded according to the 1980 Census occupation codes. Professional occupational status was used to test the proposition that respondents employed in professional occupations would have higher mean vector levels of investor risk tolerance than others.

Occupation was coded for interval level use. Occupation was coded as follows: 1 = professional (e.g., physician, manager, administrative personnel) and 0 = non-professional (e.g., technical, administrative support, service occupations, laborers, etc.). Since the sample was delimited by including only respondents who indicated currently working for pay, everyone in the sample received an occupation code. Some respondents were also classified as both professional and self-employed. One reason occupation was included as an independent variable in this analysis was that, as indicated in the review of literature, higher ranking occupational status (e.g., business executive, professional, etc.) has been found to be associated with higher levels of investor risk tolerance (MacCrimmon & Wehrung, 1986).

Self-Employment. Respondents to the 1992 SCF were also asked whether they worked for someone else, or if they considered themselves to be self-employed. Responses were sorted and coded according to the 1980 Census occupational and employment classification codes.

For the purposes of this research, self-employment status was dummy coded for interval level use as follows: 1 = not self-employed and 0 = self-employed. Self-employment status was

included as a demographic variable in this analysis, because, as the review of literature indicated, all things being equal, there is research evidence to suggest that self-employed individuals typically take greater risks and accept greater investment volatility than individuals who work on a straight salary for an employer (MacCrimmon & Wehrung, 1986; Roszkowski et al., 1993).

Income. Income was considered a continuous variable. Data for this variable were collected based on the following question: “We have talked about various sources of income. Now we would like to get the overall picture of all the different sources of income that you and members of your family living here had in 1992 ... In total, how much income did you receive in 1992, before deductions for taxes and anything else?”

Income was included as an independent variable because, according to MacCrimmon and Wehrung (1986), upper income persons tend to take higher risks than those with lower incomes. Investment managers have concluded that because individuals with high incomes have access to more immediate resources (O’Neill, 1996), increased levels of income often lead to increased levels of risk tolerance, because the consequences of investment losses impact high income earners less than low income earners.

Race. Race, a nominal level independent variable, was dummy coded for use as an interval level variable.¹³ Four new variables were recoded from six initial categories due to insufficient response rates from American Indians, Eskimos, Aleuts, Asians, and others. Respondents were coded as follows: 1 = White and 0 = not White; 1 = Black and 0 = not Black; 1 = Hispanic and 0 = not Hispanic; and 1 = Asian (including American Indian/Eskimo/Aleut/Other) and 0 = not Asian.

Race was included as an independent variable, because according to researchers such as Zhong and Xiao (1995) and Sung and Hanna (1996a), diverse cultural values, preferences, and tastes may affect the risk tolerance of ethnic groups differently. Although rarely discussed openly, there is general consensus among personal finance researchers that Whites are more risk tolerant than non-Whites. Reasons for this include: (a) non-Whites may not have the same exposure to banks and other financial institutions as Whites, (b) minority groups may be exposed to non-

¹³ Race was self-reported by each respondent. Only six categories were provided in the SCF: American Indian/Eskimo/Aleut, Asian, Hispanic, Black, White, and Other. For the public use file, American Indian/Eskimo/Aleut, Asian, and Other were combined.

traditional investment opportunities, (c) more non-White cultures tend to be oriented towards the past or present rather than oriented towards future returns (Zhong & Xiao), and (d) Whites, in general, may possess greater confidence in their analytical and decision making skills (MacCrimmon & Wehrung, 1986).

Education. Respondents were requested to answer the following question: “What is the highest grade of school or year of college you completed?” Responses were coded as actual number of years, ranging from 1 to 17, with 17 years being top coded to include graduate degrees. The education variable was considered to be continuous. Education was included as an independent variable because it has been argued by some that increased levels of education (i.e., formal attained academic training) allows individuals to assess risk and benefits more carefully than someone with less education. Higher education has been found to encourage risk taking (MacCrimmon & Wehrung, 1986), and as such, investment managers assume that increased levels of education are associated with increased levels of risk tolerance.

Table 2
Variable Definitions

Variable	Measurement
Gender	1 = male 0 = female
Age	respondent's age (18 - 87)
Marital Status	1 = married 0 = not married 1 = single but previously married 0 = not single but previously married 1 = never married 0 = other than never married
Occupation	1 = professional 0 = non-professional
Self-Employment	1 = not self-employed 0 = self-employed
Income	respondent's income
Race	1 = White 0 = not White 1 = Black 0 = not Black 1 = Hispanic 0 = not Hispanic 1 = Asian 0 = not Asian
Education	respondent's education (1 - 17)

Research Question and Research Propositions

The primary research question in this study was whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. The following research propositions were developed for use in answering this research question. The research propositions were as follows:

Proposition 1: The mean vectors associated with the three levels of investor risk tolerance are identical to one another.

Proposition 2: The mean proportion of male¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 3: The mean age of respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 4: The mean proportion of married¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 5: The mean proportion of single¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 6: The mean proportion of never married¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 7: The mean proportion of respondents employed in professional occupations¹⁴ is equal across the three investor risk-tolerance criteria groups.

Proposition 8: The mean proportion of not self-employed¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 9: The mean income of respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 10: The mean proportion of White¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 11: The mean proportion of Black¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 12: The mean proportion of Hispanic¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 13: The mean proportion of Asian¹⁴ respondents is equal across the three investor risk-tolerance criteria groups.

¹⁴ For dichotomous variables, mean is the proportion of cases with a value of 1.00.

Proposition 14: The mean educational level of respondents is equal across the three investor risk-tolerance criteria groups.

Proposition 15: Posterior classification results will be no better than classification by randomization. That is, the probability of assigning a respondent into a risk-tolerance category, given the respondent's demographic characteristics, will be no better than randomly assigning a respondent into a risk-tolerance category.

Data Analysis Method

In this study it was assumed that investment managers do not assign precise values to investor risk tolerance on a continuous variable. It was determined instead that investor risk tolerance is more likely considered to fall within one of three categories: high, average, or no risk tolerance (MacCrimmon & Wehrung, 1986; Roszkowski et al., 1993). Based on this assumption, the statistical method, discriminant analysis, was used to separate, discriminate, estimate, and classify individuals into risk-tolerance categories using respondents' demographic factors (Huberty, 1975).¹⁵

The technique of multiple discriminant analysis was first developed by Fisher in 1936 (Eisenbeis & Avery, 1972; Huberty, 1975; Klecka, 1980). The procedure has a solid foundation of previous use in the social sciences. The method can be viewed as a logical extension of multiple analysis of variance (MANOVA), because a hypothesis of equal means is tested using sample estimates of means and common variance (Huberty; Klecka; Scott, 1974). In the univariate case, random samples of observations on a single variable are taken, and a test is performed by partitioning the total sample variance into (a) pooled within-group variance about group means, and (b) the variance of the group means about the grand mean. The explained between-group variance is then compared to the unexplained within-group variance. Based on the results of this test, the hypothesis is either accepted or rejected. The univariate case can be extended easily to a multivariate situation, where the dependent variable consists of more than two categories. In the multivariate case, a linear function can be used to maximize the between-

¹⁵ "The methodology is a departure from the often-used regression models. It focuses attention on the notion that people may not think in continuous terms as they form their expectation of the future" (Scott, 1974, p. 39).

group variance of the dependent variable divided by the pooled within-group variance of the dependent variable.

As such, discriminant analysis is a technique which allows researchers to study the differences between two or more groups with respect to several variables at the same time (Klecka, 1980, p. 7). The procedure is a powerful tool because it provides insights into (a) which, if any, variables used in a model are useful in differentiating among criterion groups, (b) which variables are most effective in classifying individuals into criterion groups, and (c) how accurate a derived discriminant variable is in actually predicting outcomes (Huberty, 1975, 1994; Klecka).

Discriminant analysis techniques require that the following assumptions be made in order for the characteristics (i.e., demographic variables as used in this study) to accurately distinguish among groups (i.e., high, average, or no risk tolerance) (Eisenbeis & Avery, 1972; Huberty, 1975; Huck, Cormier, & Bounds, 1974; Klecka, 1980):

- (a) there must be two or more groups represented in the dependent variable;
- (b) there must be at least two individuals per group;
- (c) there can be as many independent variables as desired, provided that the number is less than the total number of individuals minus two;
- (d) independent variables should be measured at the interval level;
- (e) independent variables may not be linearly combined with other independent variables; and
- (f) each group (i.e., high, average, or no risk tolerance) should be drawn from a population with a multivariate normal distribution on the discriminating (independent) variables.

The following analysis results are reported in Chapter IV: (a) number of individuals in each criterion group,¹⁶ (b) means and standard deviations on each variable for each group and overall groups combined, (c) multivariate tests of significance, (d) significance test of univariate equality of group means, (e) standardized canonical discriminant function coefficients, (f) pooled within-group correlations between canonical discriminant function and discriminating variables,

¹⁶ “Sample sizes can play an important role in affecting discriminant analysis tests of significance. Specifically, for given differences among group means, large samples, *ceteris paribus*, increase the likelihood that the hypothesis of the equality of group means and dispersions will be rejected” (Eisenbeis & Avery, 1972, p. 53).

(g) a classification of results, (h) an estimate of the proportion of variance of the independent variables that is attributable to centroid¹⁷ differences, and (i) a classification matrix.

In summary, discriminant analysis was used because it encompasses both classification and inferential multivariate techniques (Eisenbeis & Avery, 1972). Discriminant analysis allowed for the testing of mean group differences and the description of overlaps among groups, and for the construction of a classification scheme based on the set of demographic variables being examined in this study. The following key assumptions underlying discriminant analysis were met through data collection methods, as outlined previously: (a) the groups being investigated were discrete and identifiable, (b) each observation was described by a set of measurements on certain variables, and (c) variables were assumed to have a multivariate normal distribution in each population (Eisenbeis & Avery).

Summary of Research Methodology

This study was designed to test whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to differentiate among levels of investor risk tolerance. The 1992 SCF was used to ascertain respondents' tolerances for different degrees of investment risks. A multiple discriminant analysis technique was utilized to test the research hypotheses. Findings from this research will be used to:

- (a) provide insights into which of the eight demographics were most significant in differentiating among and classifying someone into investor risk-tolerance categories;
- (b) go beyond purely subjective criteria related to the personal characteristics of individuals in order to define a set of operating characteristics that distinguish among high, average, and no investor risk tolerance; and
- (c) consider the implications of those demographics that do not distinguish among high, average, and no investor risk tolerance.

¹⁷ A centroid is a weighted combination of the observed dependent variable(s) in a MANOVA or discriminant analysis (Vogt, 1993). A group centroid is an imaginary point which has coordinates that are the group's mean on each of the variables. "Because each centroid represents the typical position for its group, we can study them to obtain an understanding of how the groups differ" (Klecka, 1980, p. 16).

CHAPTER IV

FINDINGS AND RESULTS

This study was designed to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. A model for categorizing investors into risk-tolerance categories using demographic factors was developed and empirically tested using data from the 1992 Survey of Consumer Finances (SCF) ($N = 2,626$).

The purpose of this chapter is to present findings and results relevant to answering the research question and associated research propositions. The chapter begins with an analysis of the demographic characteristics of the sample and a discussion of the representativeness of the sample compared to the entire SCF data set, the broader U.S. population, and special subsets of the population. This review is followed by results of the statistical tests used to empirically test the model. The following are reported: (a) number of individuals in each criterion group, (b) means and standard deviations on each variable for each group and overall groups combined, (c) multivariate tests of significance, (d) significance test of univariate equality of group means, (e) standardized canonical discriminant function coefficients, (f) pooled within-group correlations between canonical discriminant function and discriminating variables, (g) an estimate of the proportion of variance of the independent variables that is attributable to centroid differences, and (h) a classification matrix.

Demographic Characteristics of the Sample

Findings related to demographic characteristics of the sample included frequencies and means about the survey respondents. The sample also was compared to the SCF data set and the U.S. population. Reported characteristics for the sample and the SCF data set represent a household's "breadwinner," defined by the Federal Reserve Board as a male, or if no male was present, then the spouse, partner, or female head of household. Although family members may have been present at the time of the survey, only one person was asked to respond to questions.

As indicated in Table 3, the majority of respondents were male (85%). This high number of males was due to the sampling procedure used by the Federal Reserve Board. Age of respondents ranged from 18 to 87 years with a mean of 44.50 years. Approximately 70% were aged 31 to 60 years, approximately 15% aged 18 to 30, and 14% aged 61 and older. In terms of gender and age, the sample provided adequate statistical representation throughout each risk tolerance domain.

The racial and ethnic background of the sample was homogeneous in nature (Table 3). Almost 81% of respondents were White. Blacks constituted slightly more than 8% of the sample, with Hispanics (6%), Asians (4.60%), and Native Americans and others (0.30%), comprising the remainder. Although the sample distribution was skewed towards Whites, there were sufficient numbers of Black, Hispanic, and Asian respondents to allow statistical comparisons to be made across risk-tolerance groups.

As indicated in Table 3, over 72% of respondents were married or living with a partner. Almost 17% of respondents were single but previously married, including the categories of divorced, separated, and widowed, while nearly 12% of the sample had never married.

Respondents who were employed in a professional occupation were over-represented in this sample. A large number of respondents indicated being employed professionally (45%). The remainder (55%) were employed in non-professional occupations such as trade positions, skilled or unskilled vocations, clerical jobs, or other non-professional occupations.

The majority of respondents worked for someone else, such as another person or business (67%). However, approximately 33% of respondents indicated being self-employed (Table 3).¹⁸

Total household income before taxes for respondents, as shown in Table 3, ranged in value from less than zero to \$999,999. Approximately 12% of respondents had household incomes below \$49,999, while a far greater percentage of respondents (approximately 60%) had household incomes between \$50,000 and \$99,999 annually. Over 27% of respondents indicated having incomes exceeding \$100,000 a year. On average, total household income before taxes for

¹⁸ Due to the nature of the occupation and self-employment questions asked in the SCF, it was possible for a respondent to have both an occupation code and a self-employment code. It was estimated that approximately 15% of the total sample was self-employed and working in a professional occupation. However, such interactions within the data did not adversely affect the multivariate analysis used in this study.

respondents was \$112,016, with a standard deviation of \$171,520. Incomes were skewed in the sample primarily because of data collection techniques employed by the Federal Reserve Board. The SCF employed a dual-frame sample incorporating both an area-probability sample and a “special list sample” developed from IRS tax records. The area-probability sample provided information on financial variables which were broadly distributed in the population, while the special list sample specifically over-sampled households which were more likely to be wealthy (Montalto & Sung, 1996). The use of the special list sample resulted in a general right-skewed distribution of incomes in the sample.

Educational attainment of respondents ranged from less than a high school diploma to receipt of a doctorate degree or other professional certification. The majority of respondents (68%) had attained educational levels of less than a college degree (Table 3). Approximately 23% of respondents indicated having at least an Associate’s degree or a Bachelor’s degree. Nine percent of respondents indicated earning a Master’s or Ph.D. degree, or other educational certification. The range of attained educational levels of respondents was 3 years to 17 or more years. On average, respondents reported completing 14.14 years of formal education, with a standard deviation of 2.74 years.

Table 3

Demographic Characteristics of Respondents (N = 2,626)

Demographic Characteristics	Frequency	%*
Gender		
Male	2,223	84.66
Female	403	15.35
Age (in Years)		
Less Than 30	390	14.80
31 to 45	960	36.60
46 to 60	897	34.20
61 and Over	379	14.40
Marital Status		
Married	1,878	71.52
Single But Previously Married	436	16.60
Never Married	312	11.88
Occupation		
Professional	1,186	45.16
Non-Professional	1,440	54.84
Self-Employment Status		
Self-Employed	877	33.40
Not Self-Employed	1,749	66.60
Total Household Income		
Less Than \$49,999	326	12.40
\$50,000 - \$99,999	1,570	59.80
\$100,000 Or More	730	27.80
Race		
Black	219	8.34
Hispanic	152	5.79
Asian	121	4.61
Native Americans and Others	8	0.30
White	2,126	80.96
Educational Attainment (Years)		
Less Than High School	818	31.15
High School Diploma	554	21.09
Less Than College	422	16.07
Associate's Degree	131	4.98
Bachelor's Degree	473	18.01
Master's Degree	152	5.78
Ph.D. and Other Certification	76	2.89

*Percentage may not add to 100 due to rounding.

Representativeness of the Sample

A comparison was made of the characteristics of the sample to those of the SCF data set and the U.S. population (Table 4). This was done to ascertain the generalizability of the findings to broader populations. Mean results, as shown in Table 4, indicated that in certain respects the sample was representative of the U.S. population, but in other ways, the sample was very different.

Sample characteristics that were most similar to that of the United States population were racial distributions. The sample consisted of 81% White, 8% Black, 6% Hispanic, 4.70% Asian, and 0.30% Native American, compared with a U.S. population of 75% White, 13% Black, 7.5% Hispanic, and 3.50% Asian, and 1% Native American.

Sample characteristics differed from those of the U.S. population in the following categories: (a) gender, (b) age, (c) marital status, (d) percent employed professionally, (e) percent self-employed, (f) income, and (g) educational attainment. One reason for these differences may be the result of delimitations applied to the sample. For example, only subjects who indicated currently working for pay were included in the sample. This helps explain why, in general, the mean sample characteristics were higher than those of the average U.S. citizen. As a result of research delimitations, caution should be taken in the interpretation of data and in the generalization of conclusions.

More males (85%) than females (15%) were respondents in the sample, which differed from the demographic makeup of the U.S. population where males comprise 49% of the population. This over representation of males was a result of sampling techniques employed by the Federal Reserve Board. The average and median age of sample respondents (44.48 and 45 years, respectively) was lower than the average and median age of U.S. citizens (48.38 and 48 years, respectively). The lower mean age of sample respondents was a result of a delimitation in this research which removed non-employed respondents (e.g., retirees) from the analysis.

The percentage of respondents in the sample who were married was nearly 72%, with 17% single but previously married, and 11% never married, compared to 57% being married, 28% single but previously married, and 15% never married in the U.S. population. The sample also consisted of more persons who worked in a professional occupation (45%) or were self-employed (33%), compared to the U.S. as a whole (22% and 15%, respectively).

The mean total household income of respondents (\$112,016) was almost three times the mean income of the U.S. as a whole (\$38,914). The use of a special list sample by the Federal Reserve Board to select high income earners resulted in this general right-skewed distribution of respondent incomes. Finally, respondents in the sample were better educated (14.14 years) than the broader U.S. population (12.88 years).

Table 4 also provides a comparison of mean scores for the SCF data set from which the sample was taken. Sample respondents matched more closely with distributions found in the SCF data set, which was itself skewed to over-represent families with higher levels of income, education, and assets. According to Furlong (1989), Rich (1984), and Sestina (1992), the demographics of the sample also matched the typical demographic composition of investment management clientele, making findings and conclusions from this study generalizable to this group. Specifically, the typical investment management firm client, like the average respondent in the sample, tends to be a married, middle-aged White male, employed in a professional occupation, often self-employed, with a higher than average income and education.

In summary, the sample over-represented males, married individuals, professionals, and self-employed individuals. Mean income and educational levels were found to be higher than the broader population. Respondents' age profiles were slightly lower than the U.S. on average, but in terms of race, the sample matched closely with the broader population. Differences between the sample and the broader U.S. population limit the generalizability of findings to the broader population, but they do allow for generalizations to investment management clientele and to the SCF sample frame. Researchers and practitioners are cautioned not to draw generalizations from this research to populations with demographic characteristics that are significantly different from the sample's demographic composite. Limitations in the generalizability of the sample point to the need for additional research with a sample that more closely matches that of the U.S. population as well as other specialized populations.

Table 4

Comparison of Sample Mean Characteristics (N =2,626) With Those of the Survey of Consumer
Finances (1992) Data Set and the Broader U.S. Population

Demographic Characteristic	Survey %*	SCF Data Set %*	United States %*#
Gender			
Male	84.66	79.83	49.26
Female	15.35	20.17	50.74
Age (in Years)	44.48	41.66	48.38
Marital Status			
Married	71.52	65.30	57.41
Single But Previously Married	16.60	15.13	14.43
Never Married	11.88	19.57	28.15
Occupation			
Professional	45.16	33.46	22.01
Non-Professional	54.84	66.54	77.99
Self-Employment Status			
Self-Employed	33.40	16.54	14.90
Not Self-Employed	66.60	83.46	85.10
Total Household Income (\$1,000)	112.02	47.80	38.91
Race			
Black	8.34	11.46	12.72
Hispanic	5.79	7.77	7.55
Asian	4.61	4.35	3.58
Native American and Other	0.30	0.40	1.00
White	80.96	76.03	75.15
Education (Years)	14.14	13.58	12.88

*Percentages may not add to 100 due to rounding.

#Source:

U.S. Bureau of the Census (1994). Statistical Abstract of the United States: 1994. Washington DC: U.S. Government Printing Office.

The Uniqueness of the Sample and its Affect on the Statistical Analyses

It is important to note that the sample was diverse, and that each demographic characteristic examined in this study had adequate representation across all three levels of risk tolerance to conduct a multiple discriminant analysis (SAS Institute, 1990). The sampling method employed by the Federal Reserve Board assured that a wide cross-section of the U.S. population would be represented in the data set, which also enhanced the likelihood that the sample used in this research would have sufficient numbers of respondents in each demographic category to complete a multivariate statistical analysis. It also should be noted that skewness found within certain demographic characteristics of the sample (e.g., household incomes) did not adversely affect conclusions drawn from the statistical analysis. For example, the range of incomes, although skewed, was adequately distributed among classifications of risk and other variables for the purposes of this study.

However, researchers and practitioners should use caution when applying generalizations from this research to populations which differ significantly from this sample. For example, the number of non-White females in the sample was relatively low (i.e., less than 100). While this characteristic of the sample did not adversely affect the analysis, certain conclusions developed from this analysis may not be applicable to populations comprised of primarily non-White females or other under-represented groups. In summary, the sample used in this analysis best represented married, middle-aged White males, employed in a professional occupation, often self-employed, with higher than average incomes and education. Generalizing findings from this research to a population significantly different from this demographic composite is not recommended.

Discriminant analysis and interaction effects. Recall that discriminant analysis, the statistical method used in this study, classifies cases (i.e., respondents) into one of several mutually exclusive groups (i.e., high, average, or no risk tolerance) based on response values for a set of classifying variables (i.e., the independent variables analyzed in this study). Multiple discriminant analysis was chosen as the best statistical method for analyzing this sample due to possible interactions among the demographic factors. Researchers and practitioners are encouraged to keep in mind that potential interactions among variables is fully accounted for in discriminant analysis. Unlike regression procedures (e.g., ordinary least squares, logit, and probit) which require researchers to create interaction variables to account for linear combinations that

can distort conclusions, discriminant analysis provides a means for maximizing interaction effects among variables in the generation of coefficients that adequately differentiate among criterion groups.

Discriminant analysis works to maximize interactions among variables by analyzing both within-group variability and between-group variability when developing canonical discriminant functions. In other words, discriminant analysis maximizes interrelations among variables by incorporating this information into a relationship output that is summarized in a single index.

The SAS statistical software package, which was used to conduct the multiple discriminant analysis, required that at least two respondents be in each dependent variable group, across demographic characteristics, in order to accurately distinguish among groups. In each case, this minimum number was met, and in all cases, the number of respondents in each risk-tolerance category was sufficient to draw conclusions regarding group risk-tolerance membership.

Discriminant Analysis Test Results

This section reports findings from the multiple discriminant analysis test that was designed to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. All reported outcomes were developed using SAS statistical software.

Comparison of Multivariate Mean Vectors Among Levels of Risk Tolerance

The first step in the discriminant analysis required a test of the proposition that the mean vectors of the high, average, and no risk-tolerance categories were equal (i.e., Proposition 1). The test of this proposition was evaluated using the Wilks' Lambda statistic. Wilks' Lambda was calculated to be .8110 (Table 5). This was equivalent to an F ratio of 26.2262 with 22 and 5,226 degrees of freedom. The probability of obtaining an F this large by chance was less than .0001. It was determined that the independent variables, as used in the proposed model, did discriminate among levels of risk tolerance, and that the three groups were distinct.

Table 5

Canonical Discriminant Analysis Multivariate Statistics and F Approximations

Statistic	Value	F	Num DF	DF	Pr > F
Wilks' Lambda	.8110	26.2262*	22	5226	.0001

*F Statistic for Wilks' Lambda is exact.

Determination of Differentiating Variables

Table 6 provides the means and standard deviations of the three levels of investor risk tolerance (i.e., high, average, and none) on the various independent variables. Data in this table were useful in making initial determinations of which variables distinguished among the three levels of risk tolerance. However, Table 6 does not provide significance test results. Note that for dichotomous variables, the mean is the proportion of cases with a value of one. For example, 93% of respondents in the high risk-tolerance category were men, compared to 87% in the average risk-tolerance category, and 75% in the no risk-tolerance category (i.e., $\bar{X} = .9315$ for high risk tolerance, $\bar{X} = .8698$ for average risk tolerance, and $\bar{X} = .7471$ for no risk tolerance).

Table 6

Group Means and Standard Deviations of Classifying Variables

Variable*	High Risk		Average Risk		No Risk	
	Tolerance		Tolerance		Tolerance	
	Mean	SD	Mean	SD	Mean	SD
Male	.9315	.2528	.8698	.3367	.7471	.4349
Age	44.6481	12.7804	44.9283	13.1379	43.7599	13.8120
Marital Status						
Single but previously married	.1242	.3300	.1337	.3405	.2400	.4273
Never Married	.1082	.3109	.1258	.3318	.1171	.3217
Married	.7675	.4227	.7403	.4386	.6428	.4794
Professionals	.5605	.4967	.5139	.5000	.2880	.4531
Not Self-Employed	.5159	.5001	.6529	.4762	.7939	.4047
Total Household Income (\$1,000)	165.7981	202.2011	120.5484	176.7781	61.0380	117.3737
Race						
Black	.0573	.2327	.0585	.2349	.1358	.1358
Hispanic	.0366	.1879	.0349	.1837	.1042	.3057
Asian	.0382	.1918	.0472	.212	.0597	.2371
White	.8678	.3389	.8592	.3479	.7002	.4584
Education	15.1576	2.1242	14.5332	2.4945	12.8735	2.9830

*For dichotomous variables, mean is the proportion of cases with a value of 1.00.

Univariate test statistics, based on a canonical discriminant analysis, are shown in Table 7. These univariate test statistics were generated for the purpose of measuring the significance of the independent variables in differentiating among the three levels of risk tolerance. Recall that the research propositions stated that the group means among risk-tolerance levels would be equal. F-test results indicated that the following demographic characteristics were significant in differentiating among levels of risk tolerance: gender; married status; single but previously married status; professional occupational status; self-employment status; income; White, Black, or Hispanic racial background; and educational level. Three demographic characteristics, namely age, never married, and Asian, were not significant. That is, there were sufficient statistical data to fail to reject Propositions 3, 6, and 13 which stated that the mean age of respondents, the mean proportion of Asians, and the mean proportion of never marrieds across the three risk-tolerance criterion groups would be equal, respectively. The remaining equality of mean Propositions (i.e., 2, 4, 5, 7, 8, 9, 10, 11, 12, and 14) were rejected.

Table 7
Canonical Discriminant Analysis Univariate Test Statistics

Variable	Total SD	Pooled SD	Between SD	R-Squared	RSQ/ (1-RSQ)	F	Pr > F
Male	.3623	.3552	.0881	.0394	.0411	53.8533	.0001
Age	13.2825	13.2777	.6280	.0015	.0015	1.9582	.1413
Married	.4514	.4487	.0628	.0129	.0131	17.1725	.0001
Single but previously married	.3722	.3687	.0631	.0192	.0195	25.6312	.0001
Never Married	.3236	.3237	.0095	.0005	.0005	.6167	.5398
Professional	.4978	.4845	.1409	.0534	.0564	74.0160	.0001
Not Self- Employed	.4717	.4603	.1272	.0485	.0509	66.8046	.0001
Household Income	171.5197	166.9463	48.5066	.0533	.0563	73.8960	.0001
Black	.2765	.2742	.0446	.0173	.0176	23.1388	.0001
Hispanic	.2336	.2314	.0394	.0190	.0193	25.3738	.0001
Asian	.2162	.2161	.0099	.0014	.0014	1.8716	.1541
White	.3927	.3854	.0931	.0375	.0389	51.0493	.0001
Education	2.7415	2.5854	1.1202	.1114	.1253	164.3427	.0001

Average R-Squared: Unweighted = .0319453

The combination of mean vector scores (refer to Table 6) and univariate test statistics (refer to Table 7) suggested that proportionately, males were more likely to be categorized as having a high or average risk tolerance. Females were more likely to be categorized as having no risk tolerance. In relation to Whites, Blacks and Hispanics were found to have lower risk tolerances, with proportionately more Blacks and Hispanics falling into the no risk-tolerance category. Whites were proportionately more likely to be categorized as having either high or average risk tolerances. Single but previously married individuals, compared to marrieds, were more likely to be classified as having no risk tolerance. Married respondents, on the other hand,

were proportionately more likely to be categorized as having either high or average levels of risk tolerance.

Professionals and individuals who were self-employed were proportionately more likely to be classified as highly risk tolerant. Non-professionals and those who were not self-employed were more likely to be categorized as having no risk tolerance. Total household income before taxes was also found to be significant. The greater a respondent's household income, the more likely that person was to be classified as having high or average risk tolerance. Respondents with lower household incomes were proportionately more likely to be classified as having no risk tolerance. Finally, the trend in mean vector scores suggested that someone's attained educational level was positively related to increased levels of risk tolerance, with those respondents having higher attained educational levels being classified as having either high or average risk tolerance, and those with lower levels of education being classified as having no risk tolerance.

Summary. Although seven of the eight categories of demographic characteristics were significant in the univariate analysis, the univariate statistics alone did not provide enough evidence to determine which demographic factors could be used, either individually or in combination, to differentiate among risk-tolerance levels. Specifically, the univariate statistics indicated only that the three levels of investor risk tolerance differed in respect to (a) gender; (b) White, Black, or Hispanic racial background; (c) married or single but previously married marital status; (d) professional occupational status; (e) self-employment status; (f) income; and (g) educational level.

The univariate statistics (Table 7), which were similar to one-way analysis of variance calculations, indicated only that mean vector differences were present. Using the data presented in Table 6, it was possible to draw generalizations about the trend in mean vector scores, but it was not possible to state definitively that a trend was consistent across all categories. The next stage of the analysis, the development of canonical function equations, was used to determine which of the seven univariate significant demographic characteristics could be used individually or in combination to differentiate among risk-tolerance levels. The results of this analysis are reported below.

Canonical coefficients. Once it was determined that the three levels of investor risk tolerance differed significantly on the independent variables, and it was ascertained which

demographic variables were significant in differentiating among risk-tolerance categories, the derivation of total canonical structures, with accompanying coefficients, was undertaken. This step in the analysis was conducted in order to determine (a) if risk tolerance could be described by a set of characteristics, and (b) which characteristics accounted for the greatest variance among risk-tolerance levels.

Table 8 presents the total canonical structure coefficients derived in this third step of the analysis.¹⁹ The coefficients are Pearson product moment correlations between the individual independent variables and the canonical variables, without group consideration. Recall that multiple discriminant analysis always results in at least two canonical structures. The maximum number of possible structures is equal to one less than the number of criterion levels or to the number of classifying variables, whichever is smaller (Huck et al., 1974). The discriminant functions have the same variables, but the numerical coefficients associated with each function are different, indicating that the two functions do not contribute equally to successful differentiation among risk-tolerance levels. In effect, each function explains a certain percentage of the between-group variation. According to Huck et al. (1974), after the first equation explains all that it can, the second equation attempts to account for the remaining between-group variability. The first canonical function in this analysis accounted for 93.60% of the between-group variability, while the second canonical function accounted for the remainder.

¹⁹ All of the variable coefficients are reported, even though the variables age, Asian, and never married were found previously to be insignificant. Reporting of all 13 variables was done to provide a comprehensive picture of each variable's contribution to explaining between-group variability.

Table 8
Total Canonical Structure

Variable	Canonical 1	Canonical 2
Male	.471812	.046443
Age	.079064	-.162826
Married	.268651	-.100571
Single but previously married	-.319364	.276949
Never Married	-.007463	-.178313
Professional	.542604	-.299035
Not Self-Employed	-.509533	-.415666
Household Income	.542755	.285938
Black	-.298714	.325951
Hispanic	-.309085	.377627
Asian	-.088941	-.041151
White	.443150	-.431485
Education	.792291	-.123068

The coefficients presented in Table 8 give some measure as to the contribution of the variables to the discriminant functions, and some hint as to how useful each variable is in discriminating among the three levels of investor risk tolerance. However, because these are univariate calculations they do not consider the correlations and interactions among variables, and as such, researchers have come to rely on standardized canonical structures to confirm which variables contribute the most to explaining between-group variability (Huck et al., 1974).

Standardized coefficients. The next step in the analysis involved the generation of standardized canonical coefficients for the two canonical functions. Standardized coefficients are of particular value, because they allow variables to be “compared with one another so as to determine which of the classifying are most effective as classifiers within the context of the corresponding discriminant equation” (Huck et al., 1974, p. 168). Thus, the values associated with the standardized coefficients can be considered analogous to beta weights in regression analysis or scores in factor analysis.

The standardized coefficients, presented in Table 9, were developed through linear combinations of discriminating variables that best separated the three levels of risk tolerance from each other. Unlike normalized coefficients (refer to Table 8), standardized coefficients take into account correlations and interactions between and among variables. (Coefficients for White and Married are not shown because these were omitted categories during the analysis, and as such, have zero coefficients). The following discussion details how these standardized coefficients were interpreted.

Interpretation of the standardized canonical coefficients (Table 9) involved determining which demographic characteristics were most useful in defining the underlying construct of investor risk tolerance. Thus, the variables that shared the most variation with the first and second canonical structures were found to define what attribute the structure represented (Huberty, 1994). The results indicated that scores on Canonical 1 were scores on an attribute that was fundamentally comprised of education and gender, (coefficients of .6178 and .4498, respectively). The second canonical structure, Canonical 2, was defined basically by the remaining variables.

The amount of between-group variability accounted for by the first canonical structure, based on an Eigenvalue value of .2151, was 93.60%. The second canonical structure accounted for less than 7% of between-group variability. Therefore, it was determined that education and gender explained the most between-group variability, and that these two variables contributed the most towards discriminating among the three levels of investor risk tolerance. Stated another way, it was determined that investor risk tolerance, as a construct, was best described by a combination of education and gender.

Table 9

Standardized Canonical Discriminant Function Coefficients

Variable	Canonical 1	Canonical 2
Male	.449808	.167265
Age	-.119791	-.422117
Married*	-	-
Single but previously married	.072204	.422645
Never Married	.219326	-.124202
Professional	.111363	-.403219
Not Self-Employed	-.283736	-.582482
Household Income	.237194	.4283339
Black	-.168783	.439300
Hispanic	-.126721	.451591
Asian	-.124628	.001016
White*	-	-
Education	.617761	.0617401

*White and Married were omitted categories and have zero coefficients

The value of Wilks' Lambda was .8110 using all of the variables in the first standardized canonical structure. The discriminant function thus accounted from approximately 20% of the variance between groups. The values of the canonical correlations (i.e., the degree of association between the discriminant functions and the three levels of risk tolerance which can range from 0 to 1) were .4208 and .1204, respectively (Table 10). These values were statistically significant at the .0001 level.

Table 10

Canonical Correlation Test of Significance

	Canonical Correlation	Standard Error	Eigen- value	F	Num DF	Den DF	Pr > F
1	.4208	.0161	.2151	26.2262	22	5226	.0001
2	.1204	.0192	.0147	3.8432	10	2614	.0001

In summary, the standardized canonical discriminant function coefficients were used to determine the importance of each variable in optimizing the separation of the three levels of risk tolerance. Note that the signs of the coefficients, which are similar to standardized coefficients in a multiple regression analysis, relate to group centroids and can be ignored for the purposes of this research. The two most important variables, based on (a) the amount of between-group variability explained by the first canonical structure (i.e., 93.60%), (b) the relatively high loadings of certain variables on the first canonical structure, and (c) the low explanatory power of the second canonical structure, were educational level and gender. The R-squared values (refer to Table 7) for education and gender were .1114 and .0394, respectively. The amount of attained education was the best discriminating factor among levels of investor risk tolerance (Table 9).

Confirmatory analysis. The results and interpretations presented above relating to the standardized canonical coefficients were confirmed using correlations taking into account within-group differences in mean vectors. Table 11, which shows the pooled within-group correlations between the discriminant function and each of the variables, provides structured coefficients which can also be interpreted like beta weights or scores in a factor analysis. These coefficients provide an ordered magnitude of correlations with the canonical function. These data were useful in determining which variables closely approximated the discriminating power of the total function (Bailey & Unnithan, 1994). As indicated in Table 11, education and gender were the most successful factors when differentiating among membership in one of the three levels of risk tolerance, suggesting that investor risk tolerance may be a function of attained educational level and gender.

Table 11

Pooled Within-Group Correlations Between Canonical Discriminant Function and Discriminant Function and Discriminating Variables

Variable	Canonical 1	Canonical 2
Male	.441016	.163995
Age	-.119747	-.421964
Married*	-	-
Single but previously married	.071536	.418734
Never Married	.219356	-.124220
Professional	.108389	-.392450
Not Self-Employed	-.276889	-.568407
Household Income	.230870	.416913
Black	-.167377	.435641
Hispanic	-.125561	.447455
Asian	-.124586	.001016
White*	-	-
Education	.582572	.058223

*White and Married were omitted categories and have zero coefficients

Classification Results

Research Proposition 15 stated that the posterior classification results of the discriminant analysis would be no better than classification by randomization. That is, the probability of assigning a respondent into a risk-tolerance category, given the respondent's demographic characteristics, would be no better than randomly assigning a respondent into a risk-tolerance category. A generalized squared distance function, using a cross-validation summary, was used to classify subjects into one of the three levels of investor risk tolerance. The generalized squared distance function used was:

$$D_j^2(X) = (X - \underline{X}_{(X_j)})', \text{COV}_{(X)}^{-1} (X - \underline{X}_{(X_j)})$$

Posterior probability of membership in each risk category was determined by:

$$\Pr(j|X) = \exp(-.5 D_j^2(X)) / \sum_k \exp(-.5 D_k^2(X))$$

Table 12 provides the classification of results showing that out of 628 actual subjects in the high risk-tolerance category, the model was able to classify 340 or 54.14% correctly; of the 1,144 subjects actually in the average risk-tolerance category, the model was able to classify 396 or 34.62% correctly; and of the 854 subjects actually in the no risk-tolerance category, the model was able to correctly classify 532 or 62.32%. Table 13 summarizes the classification error rates of the discriminant equations. The equations were statistically significant. However, the equations led to approximately 52% of respondents being mis-classified (i.e., less than a 50% classification success rate).

Table 12
Classification of Results

	High Risk	Average Risk	No Risk	Actual Group Membership	% Correct Classifications
High Risk	340	171	117	628	54.14%
Average Risk	394	396	354	1,144	34.62%
No Risk	128	194	532	854	62.32%
Total	862	761	1003	2,626	48.29%
Percent	32.83%	28.98%	38.19%	100.00%	n.a.
Priors	33.33%	33.33%	33.33%	n.a.	n.a.

Table 13
Error Count Estimates for Risk-Tolerance Levels

	High Risk	Average Risk	No Risk	Total
Rate	.4586	.6538	.3770	.5171
Actual Priors	.2000	.4000	.4000	1.00
Random Priors	.3333	.3333	.3333	1.00

Huberty (1994) recommended a method to determine whether or not actual classification results obtained were better than those arrived at by chance. Huberty recommended using the following index to generate an improvement-over-chance descriptive statistic:

$$I = (H_o - H_e)/(1 - H_e),$$

where H_o is the observed hit rate (successful classification) and H_e is the expected hit rate by chance.

Therefore, using the proportional chance criterion for total-group classification with approximate response rates from the SCF risk assessment question (i.e., 18%, 42%, and 40% for high, average, and no risk tolerance, respectively), $H_o = 1,268/2,626 = .4829$, $H_e = 628(.18) + 1,144 (.42) + 854 (.40) = 935/2,626 = .3561$, and $I = (.4829 - .3561)/(1 - .3561) = .1969$. Using this classification rule, it was determined that 19.69% fewer classification errors would be made than if classification were done by chance (i.e., randomly assigning 18% of respondents into the high risk-tolerance category, 42% into the average category, and 40% into the no risk-tolerance category). This was determined to be a small improvement-over-chance, offering a low proportional-reduction-in-error (Huberty, 1994). A similar low improvement-over-chance was calculated using 33% prior probabilities (i.e., 23% fewer classification errors).

According to Huberty (1994) and Walters (1986), the I index may be used with any definition of chance, but in practice, the rule has generally been applied based on a minimum cutoff score of $H_e = .50$, where I must be greater than .50 in order to be meaningful. As an effect size index, the magnitude of I , using both actual and 33% prior probabilities, was determined to reflect a very low level of “meaningfulness” (Huberty, p. 108). Thus, while Proposition 15 was rejected, because the discriminant equations developed from the analysis provided better classification than could have been achieved by randomly assigning subjects into risk-tolerance categories, it also was concluded that the classification success rate of the equations offered little improvement-over-chance.

As a result, investment managers may find that using the equations as classification tools results in less than optimal classification. The procedure over classified respondents into high and no risk-tolerance levels, while under classifying respondents into the average risk-tolerance

category. The danger in this classification process is apparent in practical application. The equations classified 322 out of 854 (38%) no risk respondents into high and average categories. These false-positive classifications can lead to asset allocations that are too aggressive, which could cause some individuals who were mis-classified to sell securities at a loss (Train, 1995). In summary, the equations, while working better than by chance, should be used with caution.

Summary of Findings

This chapter began by presenting the demographic characteristics of the sample (N = 2,626) used in this analysis. A comparison of the demographic sample with the SCF data set and the U.S. population revealed that similarities with the broader population included distributions among racial classifications, but that the sample over represented males, marrieds, professionals, and the self-employed. Mean incomes and education for the sample were higher than income and education distributions found in the U.S. population. The average and median age of the sample was less than the mean and median age for the U.S. population as a whole. Thus, it was concluded that the generalizability of the results of this study to a larger population, such as the U.S. in aggregate, may be limited. However, it was determined that generalizations could be made to the sample frame. It also was concluded that the sample best represented current and prospective clients of an investment management firm, and that researchers and practitioners should be cautious in generalizing these findings to populations that don't match the general characteristics of the sample.

The discussion of demographic characteristics was followed by a reporting of the results of a multiple discriminate analysis that was used to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. It was determined, through a combination of multivariate statistics (e.g., Wilks' Lambda) and univariate test statistics, that the three levels of investor risk tolerance (i.e., high, average, and none) were significantly different, and that all of the respondent demographic characteristics except three (i.e., age, Asian racial background, and never married marital status) were significant in differentiating among risk-tolerance categories.

The two most significant differentiating variables, as determined by standardized canonical discriminant function coefficients, pooled within-group correlations, and univariate R-squares, were education and gender. It was suggested that these two variables could be used by investment managers as effective discriminating factors due to their high standardized coefficients and the amount of between-group variance explained. The variables race, marital status, occupational status, self-employment, and income were found to load higher on the second canonical discriminant function, and it was concluded that these variables were of secondary importance in discriminating among the three levels of investor risk tolerance.

The chapter concluded with a discussion of the classification equations that were developed as part of the discriminant analysis. Although the classification procedures provided better than chance classifications of subjects into high, average, and no levels of investor risk tolerance, the classification success rates of the equations were found to be below commonly accepted standards.

CHAPTER V

DISCUSSION, CONCLUSIONS, RECOMMENDATIONS, AND IMPLICATIONS

This chapter provides a discussion of the results of this study. The purpose of this research was to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. In order to answer these questions a model for differentiating among and categorizing investors into risk-tolerance categories using demographic factors was developed and empirically tested using data from the 1992 Survey of Consumer Finances (SCF) ($N = 2,626$).

Discussion of Research Findings

This section discusses findings presented in the previous chapter. Findings are discussed in the order that they were presented in Chapter IV. The chapter begins with a discussion of the demographic characteristics of the sample, with an emphasis on the generalizability of findings. This is followed by a discussion of findings related to the research question and associated research propositions. Findings related to the efficacy of the demographics as classification factors also is presented. The chapter closes with conclusions, recommendations for future research, and implications for investment managers and researchers.

Demographic Characteristics of the Sample

The average respondent, based on their demographic characteristics, was affluent. The majority of respondents were male, White, middle-aged, and married. Slightly less than 50% of the sample were working in professional occupations. Approximately 33% of the sample were self-employed. Respondent incomes ranged from less than zero to \$999,999, with an average of \$112,016. Finally, the average respondent had over 14 years of education.

The sample was similar to the broader U.S. population in the distribution of respondents according to race, but in terms of gender, age, marital status, occupational status, self-employment, income, and education the sample differed substantially from the average U.S. citizen. In general, the sample was younger, better educated, had a higher income, and tended to

be employed in professional occupations than the average American. On the other hand, the sample matched the underlying demographic distributions found in the SCF data set.

In summary, these demographic characteristics suggest that the differences between the sample and the broader U.S. population limit the generalizability of findings from this study. Specifically, findings should not be generalized to the U.S. population, but they can be generalized to the SCF sample frame. More importantly, the sample demographics match characteristics of affluent investors (Furlong, 1989; Rich, 1984; Sestina, 1992), which makes the findings of this research meaningful to investment managers in particular.

Findings from this research have relevance to investment managers, because the typical investment management firm client, like the average respondent in the sample, tends to be a married, middle-aged White male, employed in a professional occupation, often self-employed, with a higher than average income and education (Furlong, 1989; Leimberg et al., 1993; Rich, 1984; Sestina, 1992). Findings also may be of interest to investment managers in another way. Specifically, as competition increases in the investment management business, investment firms are beginning to broaden their marketing efforts to include more females, non-Whites, and individuals with varying levels and types of education, income, and occupational classifications (Furlong). Findings from this study should help investment managers target their marketing efforts more closely to match each market segment's general risk-tolerance level.

Discriminant Analysis Research Findings

The empirical model used in this study clarified the role of gender, age, marital status, income, occupation, self-employment, race, and education in discriminating among levels of investor risk tolerance. These demographics were shown to have a direct effect in differentiating among levels of risk tolerance and in classifying individuals into different risk-tolerance categories. The purpose of this research was to determine whether these demographic variables could, in practice, be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. Findings from the test of the empirical model are discussed below.

The empirical model was tested utilizing a multiple discriminant function analysis using SAS statistical software. The dependent variable, investor risk tolerance, was measured using

three levels of risk tolerance (i.e., high, average, and none). Eight categories of demographics were used as independent variables.

A test of the equality of group centroids (tested with the Wilks' Lambda statistic) indicated that the independent variables did differentiate among levels of risk tolerance, and that the three levels were indeed distinct from each other. Canonical discriminant analysis univariate test statistics were then used to measure the significance of the independent variables in differentiating among the three levels of risk tolerance. Recall that the research propositions stated that the group means across risk-tolerance levels would be equal. Univariate test statistics showed that all but three demographic characteristics were significant in differentiating among levels of risk tolerance. Specifically, age, Asian, and never married were not significant.

The trend in mean vector scores (refer to Table 6) suggested that proportionately, males were more likely to be categorized as having either a high or average risk tolerance. Females were more likely to be categorized as having no risk tolerance. In relation to Whites, Blacks and Hispanics were found to have lower risk tolerances, with proportionately more Blacks and Hispanics falling into the no risk-tolerance category. Whites were proportionately more likely to be categorized as having either high or average risk tolerances. Single but previously married individuals, compared to marrieds, were more likely to be classified as having no risk tolerance. Married respondents, on the other hand, were proportionately more likely to be categorized as having either high or average levels of risk tolerance.

Professionals and individuals who were self-employed were significantly more likely to be classified as highly risk tolerant. Non-professionals and those who were not self-employed were more likely to be categorized as having no risk tolerance. Total household income before taxes was also found to be significant. The greater a respondent's household income, the more likely that person was to be classified as having either a high or average risk tolerance. Respondents with lower household incomes were significantly more likely to be classified as having no risk tolerance. Finally, the trend in mean vector scores suggested that someone's attained educational level was positively related to increased levels of risk tolerance, with those respondents indicating higher attained educational levels being classified as having either a high or average risk tolerance, and those with lower levels of education being classified as having no risk tolerance. These findings are discussed in more detail below.

Gender. According to Slovic (1966), there is a prevalent belief in our society that men take greater risks than women. In relation to investor risk tolerance, this research confirmed Slovic's assertion. The mean proportion of men, compared to women, in the high, average, and no risk-tolerance levels was 93%, 87%, and 75%, respectively. These mean distributions indicated that the probability of a man being in a high or average risk-tolerant category was substantially higher than for a woman. Alternatively, women were proportionately more likely to be classified into the no risk-tolerance category as compared to men.

The results of this research confirmed similar findings by Hawley and Fujii (1993-1994), Sung and Hanna (1996b), and Xiao and Noring (1994) each of whom used the SCF to determine that men were more willing than women to take financial risks. These findings also supported similar findings of Bajtelsmit and Bernasek (1996), Dreyfus (1997), and Lytton and Grable (1997) who concluded that women choose more conservative investments than men, and that men have higher risk tolerances in relation to financial management strategies compared to women.

Age. Investment managers often use age as a proxy for time as well as a measure of someone's ability to recoup financial losses. It has been widely assumed and reported that older individuals have less time to recover financial losses than do younger individuals, which has led to the assumption that older investors tend to have lower risk tolerances than younger investors. The results of this research challenge these assumptions. Results from this analysis did suggest that any conclusion that increasing age automatically leads to lower investor risk tolerance may be incorrect.

Age was not found to be a significant factor in differentiating among levels of investor risk tolerance or in classifying individuals into risk-tolerance categories. The mean age of respondents in the high, average, and no risk-tolerance categories was 45 years, 45 years, and 44 years, respectively. These mean scores, although not significant, showed an interesting pattern that runs contrary to popular opinion. Investment managers have used age to classify investors into risk-tolerance categories on the assumption that older individuals are less risk tolerant compared to younger individuals. Results from this study indicated exactly the opposite, which substantiated a conclusion made by Grable and Joo (1997) who found that, even though the trend in mean scores was not statistically significant, older individuals actually had higher risk tolerances as compared to younger persons.

The belief that increasing age automatically leads to increasing conservatism in relation to investments may be incorrect. Findings from this research suggest that there is no cause and effect linkage between age and comfort with financial risk (Cutler, 1995). In the words of Cutler, it appears that it may be a “myth to believe that age has an across-the-board effect on financial attitudes” (p. 37).

Marital status. Previous research concerning the influence of marital status in differentiating among levels of investor risk tolerance has been contradictory. Some researchers and practitioners have argued that non-married individuals have more risk tolerance than similar married individuals, while others have suggested that married individuals, not singles, possess greater risk-taking propensities. Still others have indicated that no relationship exists between marital status and investor risk tolerance.

The findings from this research suggest that in certain respects marital status is a significant factor in differentiating among levels of investor risk tolerance and in classifying individuals into risk-tolerance categories. Married and single but previously married (including the categories of divorced, separated, and widowed) marital status were found to be statistically significant, but the demographic category, never married, was not.

Married respondents were proportionally more likely to fall into the high and average levels of risk tolerance. The mean proportion of cases in the high, average, and no risk tolerance categories for marrieds was 77%, 74%, and 64%, respectively. Compared to marrieds, single but previously married respondents were less likely to be in either the high or average risk level. It was considerably more probable that respondents who were single but previously married would be classified into the no risk-tolerance category. Mean proportions of single but previously married respondents in each risk level were 12%, 13%, and 24%, respectively. Respondents who were never married made up the remaining proportions in each category.

These conclusions, similar to research findings presented by Masters (1989) and Mugenda, Hira, and Fanslow (1991), run counter to working discriminating assumptions used by some investment managers. Divorced, separated, and widowed individuals were found to be proportionately more conservative than married persons. This suggests that married individuals may have less to lose, both psychologically and financially, than divorced, separated, and widowed persons when making investment choices.

Occupation. Occupational status was used to measure differences in levels of respondents' investor risk tolerance. Professional occupational status included over 100 occupations as classified by the U.S. Census. For example, professional occupations included attorneys, physicians, managers, and college professors. Professional occupational status was found to be a significant differentiating factor. The proportion of professionals in the high, average, and no risk-tolerance categories was 56%, 51%, and 29%, respectively. These mean vector scores suggested that professionals tended to fall into either the high or average risk-tolerance category. Fewer professionals, proportionately, were found in the no risk-tolerance category. A discussion of these findings follows the description of the self-employment category.

Self-Employment. The second variable used to measure occupational effects on risk tolerance was self-employment status. Approximately 33% of the sample was self-employed. The mean proportion of those who were self-employed in the high, average, and no risk-tolerance categories was 48%, 35%, and 21%. These mean scores suggested that being self-employed could be used to differentiate among levels of risk tolerance, with self-employed individuals being more likely to be categorized as having high and average levels of risk tolerance. Respondents who were not self-employed were, proportionately, more likely to be classified as having no risk tolerance.

Results obtained from testing occupation and self-employment status supported findings by others who have found that persons employed in occupations like business ownership, management, medicine, and law tend to be willing to take more financial risks than individuals employed as clerical workers and laborers (e.g., Barnewall, 1988; Haliassos & Bertaut, 1995; Lee & Hanna, 1995; Masters, 1989; Quattlebaum, 1988; Sung & Hanna, 1996a, 1996b). A relationship appears to exist indicating that individuals can be classified into risk-tolerance categories based on their occupation and self-employment status. In summary, individuals with high or average levels of risk tolerance are more likely to be employed in professional occupations or self-employed, while individuals who have no risk tolerance are more likely to be employed in non-professional occupations or be employed by others.

Income. According to MacCrimmon and Wehrung (1986), upper income persons tend to have higher levels of risk tolerance compared to individuals with lower incomes. Results of this study support this assertion. Income was measured by the respondent's total household income

before taxes. The mean income for high, average, and no risk-tolerance categories was \$165,798, \$120,548, and \$61,038, respectively. These mean scores indicated that the higher a respondent's income, the more likely that person was to be classified into either the high or average level of risk tolerance. Lower income respondents were proportionately more likely to fall into the no risk-tolerance category.

These results supported similar findings of Blume (1976), Cohn et al. (1975), and Schooley and Worden (1996) who concluded that individuals with higher annual incomes were more likely to take greater investment risks compared to those with lower incomes. Other researchers who have used the SCF have arrived at similar conclusions. Hawley and Fujii (1993-1994), Lee and Hanna (1991), Xiao and Noring (1994), and Riley and Chow (1992) also determined that risk tolerance varies systematically with levels of income, and that in general, income can be used as a factor in differentiating among levels of risk tolerance, because individuals with higher incomes may have access to more immediate resources, allowing them to endure market fluctuations.

Race. Four categories of race were measured and included in this research. The categories of White (omitted category), Black, and Hispanic were found to be significant factors in differentiating among levels of investor risk tolerance. The category Asian was not.

The mean proportion of Whites in the high, average, and no risk-tolerance categories was 87%, 86%, and 70%, respectively. These mean scores suggested that Whites were proportionately more likely to be classified as having high or average levels of risk tolerance. Compared to Whites, Blacks were more likely to be classified as having no risk tolerance. The proportion of Blacks in the high, average, and no risk-tolerance levels was 6%, 6%, and 14%, respectively. Hispanics also were less risk tolerant compared to Whites. The proportion of Hispanics in the high, average, and no risk-tolerance levels was 4%, 3%, and 10%, respectively. The remaining proportions, although not significant as differentiating factors, were comprised of Asians (as defined in this study). These findings supported research conclusions advanced by Haliassos and Bertaut (1995), Hawley and Fujii (1993-1994), Lee and Hanna (1995), and Sung and Hanna (1996a) each of whom found that Whites had the highest probability of taking investment risks.

The lack of an investing culture in Black and Hispanic families may be part of the disparity in risk tolerances among Blacks and Hispanics (Ariel Capital Management, 1997). According to Zhong and Xiao (1995) and Sung and Hanna (1996a), different cultural values, preferences, and tastes may affect the risk tolerances of Whites and non-Whites. Zhong and Xiao suggested that non-Whites may not have the same exposure to banks and other financial institutions, and that minority groups may be exposed to non-traditional investment opportunities. It also has been suggested that Whites, in general, may possess greater confidence in their analytical and decision making skills that lead them to higher levels of risk tolerance (Ariel Capital Management; MacCrimmon & Wehrung, 1986).

Education. According to Leimberg et al. (1993), “the best investment, bar none, is education” (p. 15). Differences among investor risk-tolerance levels may lie in an awareness of what has happened in the past, and what is likely to occur in the future. This contention was supported by the findings of this research. A respondent’s educational level was found to be a significant factor in differentiating among levels of investor risk tolerance. The mean education for respondents in the high, average, and no risk-tolerance categories was 15.16 years, 14.53 years, and 12.87 years, respectively. These mean vector scores indicated that the higher a respondent’s education, the greater the likelihood of being classified into either the high or average risk-tolerance category. Respondents with lower attained educational levels were more likely to be classified as having no risk tolerance.

These results confirmed conclusions from other researchers who have found that individuals who have less than a college degree were less likely to hold risky assets such as stocks, compared to individuals with at least a college degree (e.g., Haliassos & Bertaut, 1995; Sung & Hanna, 1996b; Zhong & Xiao, 1995). In other words, education appears to encourage risk taking, because increased levels of attained academic training allows individuals to assess risks and benefits more carefully than someone with less education.

Summary. Although seven of the eight categories of demographic characteristics were significant in the univariate analysis, the univariate statistics alone did not provide enough statistical evidence to suggest the continued use of most commonly used demographic based risk-tolerance heuristics. Specifically, the univariate statistics indicated only that the three levels of investor risk tolerance differed in respect to (a) gender; (b) White, Black, and Hispanic racial

background; (c) married or single but previously married marital status; (d) professional occupational status; (e) self-employment status; (f) income; and (g) educational level.

The univariate statistics, similar to one-way analysis of variance calculations, indicated only that mean vector differences were present. Using the data presented in Table 6, it was possible to draw generalizations about the trend in mean vector scores, but it was not possible to state definitively that a trend was consistent across all categories. The next stage of the analysis, the development of canonical function equations, was used to determine which of the seven univariate significant demographic characteristics could be used individually or in combination to differentiate among levels of risk tolerance. The results of these tests are reported below.

Canonical Function Research Findings

Standardized canonical coefficients were calculated to determine the linear combination of discriminating variables that best separated the three levels of risk tolerance from each other. Using all of the variables, the value of Wilks' Lambda was .8110. Thus, the discriminant functions accounted for approximately 20% of the variance between risk-tolerance groups. The values of the canonical correlations (i.e., the degree of association between the discriminant functions and the three levels of risk tolerance) were .4208 and .1204, respectively. These values were statistically significant at the .0001 level (refer to Table 10).

Standardized canonical discriminant function coefficients were used to determine the importance of each variable in optimizing the separation of the three levels of risk tolerance. The standardized canonical coefficients that loaded the highest on the first canonical structure, which accounted for 93.60% of between-group variability, were education and gender. Race, marital status, occupational status, self-employment, and income coefficients, while statistically significant, were found to explain less between-group variability, and thus, it was determined that these variables contributed less to differentiating among levels of investor risk tolerance.

It was concluded that classes of risk tolerance differed most widely on educational level and gender. The R-squared values for these variables were .1114 and .0394, respectively. The amount of attained education was the best discriminating factor among levels of investor risk tolerance.

A pooled within-group correlations between the discriminant function and each of the variables tested was conducted to confirm these findings. The pooled within-group correlations

provided an ordered magnitude of correlations with the canonical function, which was used to determine which variables closely approximated the discriminating power of the total function. Again, education and gender were the most successful factors when differentiating among membership in the three levels of risk tolerance.

Classification Results

After determining which variables were significant factors in differentiating among risk-tolerance categories, a generalized squared distance function, using a cross-validation summary, was used to classify subjects into one of the three levels of investor risk tolerance. This test was undertaken to determine whether the independent variables could be combined into a classification formula to classify individuals efficiently and effectively into one of the three levels of investor risk tolerance.

Classification results indicated that out of 628 actual subjects in the high risk-tolerance category, the model was able to classify 340 or 54.14% correctly; of the 1,144 subjects actually in the average risk-tolerance category, the model was able to classify 396 or 34.62% correctly; and of the 854 subjects actually in the no risk-tolerance category, the model was able to correctly classify 532 or 62.32% correctly. It was determined that the discriminant equations developed from the analysis provided better classification than could have been achieved by randomly assigning subjects into risk-tolerance categories. However, overall, the classification equations achieved a 20% improvement-over-chance, less than the minimum cutoff of a 50%. Based on Huberty's (1994) *I* index, this was determined to be a small improvement-over-chance, offering a low proportional-reduction-in-error.

Although the classification procedure was efficient, it was not found to be overwhelmingly effective. The classification procedure offered only a 20% improvement-over-chance which was far below the minimum cutoff of 50% as proposed by Huberty (1994) and Walters (1986). Using the classification equations to assign someone into a risk-tolerance category would not have provided investment managers with sufficient discriminating power. The procedure over classified respondents into high and no risk-tolerance levels, while under classifying individuals into the average risk category. It was determined that these false-positive classifications could lead to inappropriate investment allocations for those individuals who were mis-classified.

Conclusions

Several conclusions emerged from the findings and resulting discussion of this study. First, the demographic characteristics of the sample differed enough from the broader U.S. population to preclude making generalizations from the sample to the broader population, but it was determined that the sample characteristics provided a profile of current or prospective investment management clientele. Specifically, the sample best represented married White males, who were professionally employed, with higher than average incomes and education. Researchers and practitioners were cautioned not to generalize findings from this research to other populations which differ significantly from this sample.

Second, several respondent demographics were found to be statistically significant in differentiating among levels of investor risk tolerance (i.e., gender, married or single but previously married marital status, professional occupation status, self-employment status, income, White, Black, or Hispanic racial background, and education). Three demographic characteristics were not found to be significant factors (i.e., age, Asian racial background, and never married marital status).

Third, it was concluded that the two most significant demographic factors, both in terms of differentiation and classification, as determined by standardized canonical discriminant function coefficients, pooled within-group correlations, and univariate R-squares, were educational level and gender. It was determined that respondents with high attained educational levels were proportionately more likely to be classified as having either average or high risk tolerances. Males were also found to be proportionately more risk tolerant than females. Of these two variables, the single most important factor was education.

Fourth, analysis revealed that the classification equations presented in Chapter IV provided better grouping of subjects into one of the three risk-tolerance categories than could have been achieved by randomly assigning subjects into risk-tolerance categories. However, it was also concluded that although the classification procedure was efficient, it was not found to be practically effective. The achieved classification procedure offered only a 20% improvement-over-chance which was found to be far below the minimum cutoff of 50%. This indicated that the use of the demographic variables in a formula to classify someone into a risk-tolerance category

would not provide investment managers with sufficient discriminating power. The procedure over classified respondents into high and no risk-tolerance levels, while under classifying individuals into the average risk-tolerance category leading to unacceptable levels of false-positive classifications.

Finally, the demographic variables explained approximately 20% of the variance in risk-tolerance differences. It was determined that these demographics (individually and in combination) provided an incomplete method for differentiating among and classifying individuals into risk-tolerance categories. Demographic characteristics appear to provide only a starting point in assessing investor risk tolerance. As the results of this study indicate, understanding risk tolerance is a complicated process that goes beyond the exclusive use of demographics.

Recommendations for Future Research

The following recommendations are suggested for future research in the field of investor risk-tolerance measurement and assessment. These recommendations are based on the results, delimitations, and limitations of this study.

1. Replicate the study using the 1989 SCF and any later versions of the SCF. More empirical testing of the risk-tolerance levels offered in the SCF needs to be examined in a multivariate manner in order to confirm the findings of this research.
2. Due to the limitations found in the sample, it is recommended that additional research be conducted in the replication of this study using samples that match more closely with the U.S. in general, as well as groups which include more non-Whites, females, and individuals with lower than average incomes and educational levels. The results from such studies would be useful in expanding generalizations of the conclusions found in this research.
3. Replicate the study using only demographic characteristics found to load highly on the canonical structures developed in this study. Future research should use education, gender, self-employment status, and income as classification factors. Use of these

demographic characteristics in the development of classification equations may lead to a substantial improvement-over-chance classification.

4. Replicate the test of the empirical model using direct surveys rather than relying on a preexisting data set. This will allow researchers to confirm the findings of this study using methods which are more directly controllable by the researcher.
5. Replicate the test of the empirical model using a wider variety of differentiating and classifying factors, such as attitudes, behaviors, and other socio-economic characteristics. This type of replication will help determine the importance of other factors in differentiating among levels of risk tolerance, and by utilizing a discriminant analysis rather than more widely used regression procedures, issues of interactions between and among variables can be reduced, leading to better classification procedures.
6. Replicate the study, using either the SCF or a direct survey, with different demographic combinations. For example, several demographics were omitted from this research that might be included in further studies (e.g., birth order). Future studies also should include expanded occupational categories in order to assess whether there are broader differences within occupational groups.
7. Further research should be conducted to test the validity of the SCF's risk assessment question. The risk-tolerance measure used in the SCF has been, almost by default, accepted by researchers as being valid, and as of this writing, the criterion related validity of the measure has yet to be tested. However, there is sufficient evidence from other research to suggest that a single risk assessment measure may not accurately capture the multidimensional nature of investor risk tolerance (MacCrimmon & Wehrung, 1986).
8. Future empirical tests of investor risk tolerance also should include longitudinal studies. Previous risk tolerance research has tended to rely on cross-sectional assessments. However, cross-sectional assessments do not provide a way to

determine if risk tolerance constitutes a fixed personality attribute or whether risk tolerance fluctuates as a result of personal or economic changes.

9. Future research should explore the reasons why certain demographics are or are not effective factors in differentiating among levels of risk tolerance. This study has reported only on the results of a quantitative test, and the results presented provide only a brief explanation as to why certain demographics are useful in differentiating among levels of investor risk tolerance. Qualitative methods would be an ideal way to examine the underlying reasons that make certain demographics effective in differentiating and classifying factors.

Implications

The purpose of this study was to determine whether the variables gender, age, marital status, occupation, self-employment, income, race, and education could be used individually or in combination to both differentiate among levels of investor risk tolerance and classify individuals into risk-tolerance categories. It was anticipated that findings and conclusions would enhance the ongoing discussion concerning the use of demographics as investor risk-tolerance classification factors, and provide investment managers with an estimate of which demographics are statistically significant for use in assessing their clients' risk preferences during the input phase of the investment management planning process.

This research endeavor was successful in addressing the dual purpose of the study. First, seven of the eight demographic characteristics were found to be effective in differentiating among levels of risk tolerance, and second, demographic variables were found to work, both individually and in combination, to classify individuals into risk-tolerance categories. The following discussion details the implications these findings have for investment managers and researchers.

Recall from Chapter I that investment managers have been taught to rely on demographics to differentiate among levels of risk tolerance and to classify investors into risk-tolerance categories. Findings from this study indicate that some demographic characteristics do work in helping investment managers differentiate and classify. However, results also suggest that some demographic characteristics work better than others. Assuming that investment managers will

continue to use demographic factors in the future, clarification of which ones work the most effectively is needed. Based on the results of this study, the following two demographics, presented in a heuristic form, are offered as the most effective differentiating factors:

- (a) individuals with greater levels of attained education are proportionately more likely to have higher risk tolerances than individuals with lower attained educational levels, and
- (b) men tend to be proportionately more risk tolerant than women.

Investment managers are cautioned to note that the most widely used demographic in differentiating among levels of risk tolerance and in classifying investors into risk-tolerance categories, a person's age, was not found to be significant. This has important implications for investment managers. For instance, relying on age as a factor in classifying someone into a risk-tolerance category, without taking into account other factors, such as income, education, occupation, and other objective client attributes, works no better than classification by random selection.

In effect, investment managers who continue to rely on age as a useful differentiating and classifying factor, run two risks. First, it is likely that current and prospective clients will be placed into a risk-tolerance category that is incorrect. This is called a false-positive classification, which may lead to extreme portfolio allocations for those clients who are classified incorrectly (especially in those cases where someone is incorrectly classified into a high or no risk-tolerance level). Second, the use of age as a differentiating factor may ultimately lead to what Palsson (1996) called a dispersion in wealth and welfare, because clients who are mis-classified may (a) sell at a loss if incorrectly classified into a higher risk category, or (b) fail to meet goals and objectives if wrongly classified into a lower risk category. In either case, the fiduciary credibility of an investment manager who uses age as a differentiating and classifying factor may be questioned.

Instead of relying on statistically insignificant demographic factors, such as age, to differentiate among levels of risk tolerance and to classify individuals into risk-tolerance categories, investment managers would be better advised to use demographic variables which optimize the separation of the three levels of risk tolerance. As discussed above, the variables of educational level and gender appear to offer the best discriminating power when used to determine into which level of risk tolerance a current or potential client will most likely fall. For

those investment managers who want to use only one demographic factor to differentiate among levels of risk tolerance, the education variable is the optimal factor.

Researchers and practitioners are cautioned not to apply generalizations from this study to populations which differ significantly from the sample. The sample best represented a married, middle-aged White male, employed in a professional occupation, often self-employed, with a higher than average income and education. It was concluded that this representation matched that of investment management clientele. It was also noted that while the diversity within the sample was sufficient to conduct the multiple discriminant analysis and draw conclusions regarding group risk-tolerance differences, the relatively low representation of certain demographic groups (e.g., Black females) restricts broader generalizations, and as such, future research should be conducted to determine if the conclusions developed from this research apply to other samples as well.

The final implication from this research involves the importance that investment managers should place on demographics during the input phase of the investment management process. Overall, the demographic variables examined in this study explained approximately 20% of the variance in risk-tolerance differences, leaving 80% of total variance in risk-tolerance difference unexplained. Demographics were found to provide an incomplete picture of respondents' risk tolerances.

Investment managers and researchers should take this last finding to heart. Demographic characteristics appear to provide only a starting point in assessing investor risk tolerance. As the results of this study indicate, understanding risk tolerance is a complicated process that goes beyond the exclusive use of demographics. More research is needed to determine which additional factors, such as expectations, attitudes, preferences, family background and culture, and financial stability factors, can be used by investment managers to increase the explained variance in risk-tolerance differences.

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