

REASSESSING THE ASSESSMENT: EXPLORING THE FACTORS THAT CONTRIBUTE
TO COMPREHENSIVE FINANCIAL RISK EVALUATION

by

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B.S., Virginia Tech, 2001
M.S., Indiana University, 2006

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Personal Financial Planning
College of Human Ecology

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Abstract

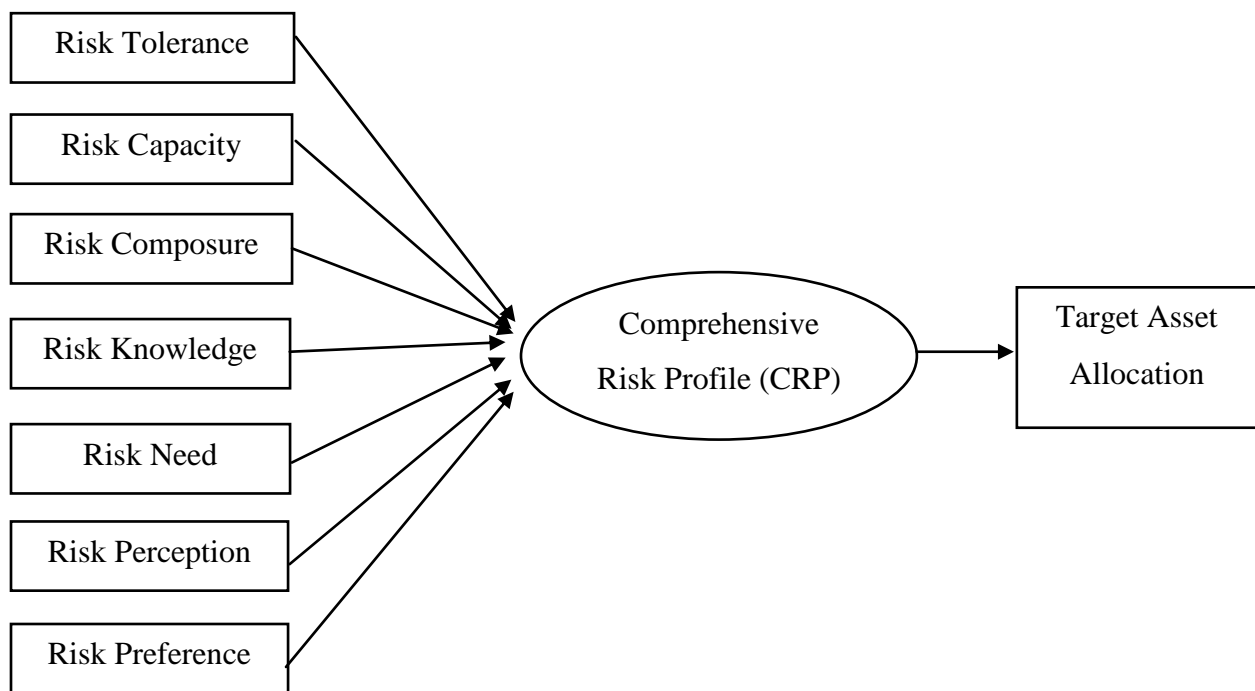
This dissertation explores the personal financial planning risk-assessment process.

Specifically, the study has five main purposes:

1. *Explore the associations among independent risk-assessment variables.*
2. *Explore the concept that prudent financial risk-assessment goes beyond estimating an individual's risk tolerance.*
3. *Explore the impact that each risk variable has on an individual's overall Comprehensive Risk Profile (CRP).*
4. *Construct a comprehensive method of risk-assessment to estimate an individual's overall risk profile.*
5. *Develop a weighted risk profile score and assign it to a target asset allocation model.*

Risk-assessment is one of the most instrumental components of the financial planning process. Financial planners and advisors have a fiduciary, as well as a suitability, responsibility to assess the level of risk individuals should bear with respect to their financial plan (Morse, 1998). Because of this, the evaluation of one's risk profile impacts the success of an individual's financial plan. If the risk-assessment is accurate, financial goals will have a higher likelihood of being met. To date, little research in the personal financial planning field has attempted to model financial risk-taking behavior in a way that is useful for practitioners, academics, and policy makers. The literature has tended to focus on either models of risk-taking rooted in economic utility theory, or tests of hypotheses related to the association among demographic and socioeconomic factors and risk-taking (Grable & Lytton, 1998). Traditional economic models do

not fully account for the role that personal, behavioral, and environmental factors play in influencing individuals' behavior beyond maximizing their expected utility (Hanna & Chen, 1997). Researchers have yet to develop a risk-profiling system that uses these behavioral or personal factors, to describe an individual's financial risk-taking framework. Ultimately, the results of this study will lead to a multidimensional, comprehensive, accurate method of risk-assessment for both academic researchers, as well as practitioners. The following will serve as the empirical model for the study.



The Empirical (Operationalized) Model for the Comprehensive Risk Profile

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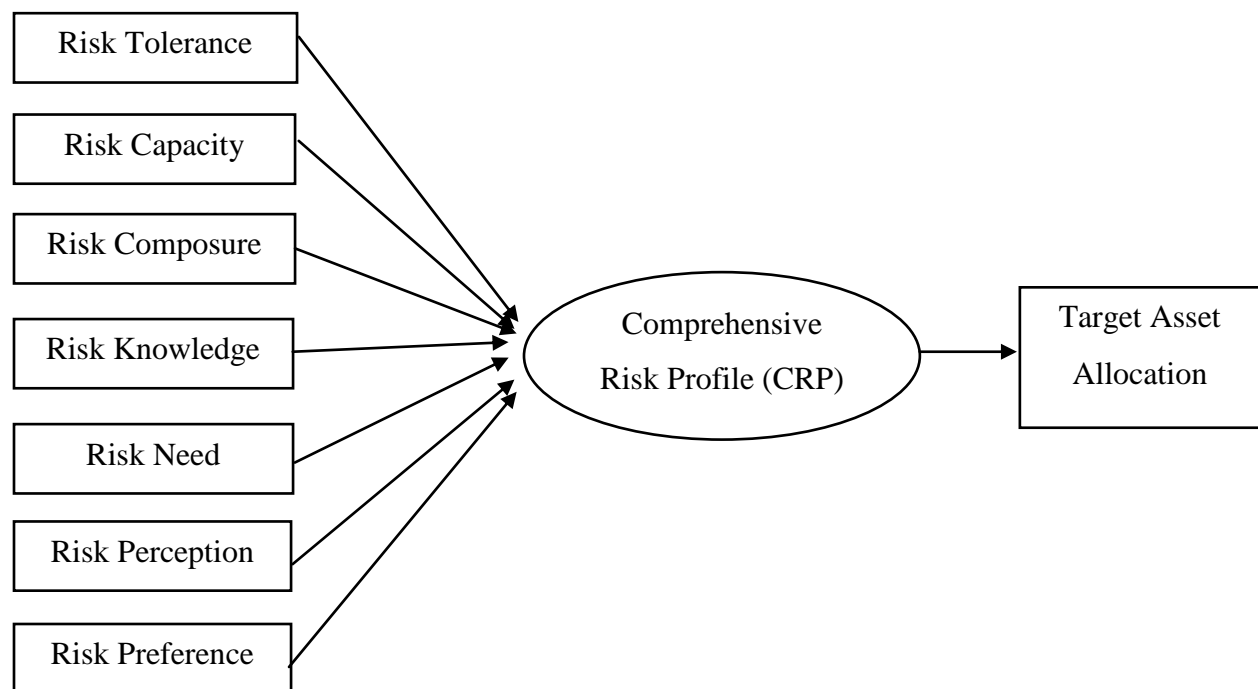
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The Empirical (Operationalized) Model for the Comprehensive Risk Profile

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Chapter 1 - Introduction

The Importance of Risk-Assessment in the Financial Planning Process

Risk-assessment is one of the most instrumental data gathering and implementation components of the financial planning process. The assessment of a risk profile is vital to an individual's financial plan and proper asset allocation (Roszkowski & Davey, 2010). Many times individuals' preferences and needs are different than the actual decisions that they make. If individuals make short-term investment decisions that are inconsistent with their long-term goals and needs, poor investment performance may take place. Financial planners and advisors have a fiduciary, as well as a suitability responsibility, to assess the level of risk individuals should bear with respect to their financial plan (Morse, 1998). Because of this, the evaluation of one's risk profile impacts the success of an individual's financial plan. If the risk-assessment is accurate, financial goals will have a higher likelihood of being met. For example, if the risk-assessment process is accurate, individuals' financial plans will be more likely to fit their needs and personalities, thus increasing the likelihood that they will experience successful outcomes. If the risk questions are not answered (or asked) correctly, the entire financial plan could result in missed expectations, misunderstanding, and disappointment (Moreschi, 2005).

To date, little research in the personal financial planning field has attempted to model financial risk-taking behavior in a way that is useful for both practitioners and policy makers. The literature has tended to focus on either models of risk-taking rooted in economic utility theory, or tests of hypotheses related to the association among demographic and socioeconomic factors and risk-taking (Grable & Lytton, 1998). Traditional economic models do not fully account for the role that personal and environmental factors play in influencing individuals' behavior beyond maximizing their expected utility (Hanna & Chen, 1997). Researchers have yet

to develop a risk-profiling system that uses these behavioral or personal factors to describe an individual's financial risk-taking framework. Methods have ranged from choice dilemmas (Wallach & Kogan, 1959) to single-item risk surveys (the Survey of Consumer Finance risk question) to multidimensional measures (Barsky, Juster, Kimball, & Shapiro, 1997; Grable & Lytton, 1999; Hanna & Lindamood, 2004). To combat the elusiveness of the risk-assessment process, strategies that include clear risk definitions, separation of risk constructs, and the incorporation of situational influences on risk are needed to more accurately assess individuals' risk propensities (Fox & Tannenbaum, 2011).

Knowing that there may be flaws in the ways risk profiles have traditionally been assessed, the exploration of new components to use is underway (Bouchey, 2004). Earlier research has found that adding a behavioral construct to the assessment process may increase the validity of the risk estimate (Hanna, Waller, & Finke, 1998). In addition to the concepts associated with Modern Portfolio Theory (MPT) and the rational investor, individuals are also influenced by emotions and behavior. Although current methods of risk-assessment and traditional risk frameworks assume that individuals are nearly always rational, and emotions mean little to the decision-making process, the literature shows that this is not always true. Lowenstein (2000) claimed that feelings and emotions experienced at the time an individual is making a financial decision influence the choice. More specifically, Lucey and Dowling (2005) argued that individuals' mood is especially significant in the risk decision process. They found that people who are in a good mood are more likely to be optimistic when making a risk decision, and vice-versa. Other studies noted similar findings (Grable, 2000; Grable & Roszkowski, 2008; Santacruz, 2009). Traditional models like the Capital Asset Pricing Model (CAPM) do not take these kinds of emotions into consideration. Mood is not the only emotion

relevant in the risk decision-making process. Loomes and Sugden (1982) were among the first to address regret in the decision-making process. Their framework explains that individuals are more apt to consider regret when given a choice, ultimately influencing them to make a more pessimistic selection. Benartzi and Thaler (1995) applied this logic to their myopic loss aversion theory. The risk-as-feelings framework (Lowenstein et al., 2001) also considers emotions in the risk decision. Further, the model illustrates how emotions cannot just influence, but dictate, the decision process. Other studies have found that emotions play an integral role when an individual is making a choice (Ackert, Church, & Deaves, 2003; Barber & Odean, 2001; Cavalheiro, Vieira, Ceretta, Trindade, & Tavares; Forgas, 1995; Lo & Repin, 2002; Nofsinger, 2005; Thaler, 2000; Wright & Bower, 1992).

Risk-assessments affect regulators, as well as those subject to fiduciary and suitability standards. This means that a financial planner, consultant, Registered Investment Advisor, or any person or institution viewed as a fiduciary is held to the fiduciary standard. The fiduciary standard is part of the code of conduct for many brokers, dealers, and investment advisors. It states that that when providing personalized financial/investment advice to clients, advisors should act in the best interest of the client, without regard to the financial or other interest of the person providing the advice (Finke & Langdon, 2012). Additionally, a financial advisor is considered a fiduciary in the following situations:

- When the advisor/planner has discretion over client assets;
- When the client is dependent on the advisor/planner's advice;
- When the advisor/planner is providing the client with comprehensive and continuous advice;
- When the advisor/planner is providing an ERISA client advice, and is receiving a fee; and
- When the advisor/planner is a Registered Investment Advisor (RIA)

Risk-assessment is an important element in the pursuit of fiduciary compliance. Specifically, assessing clients' understanding of their risk and reward tradeoff performance is a central job of the fiduciary. This process speaks to the loyalty of the advisor to the client, and the ability of the client to achieve his/her financial goals and objectives. Many times individuals have no concept of the amount of risk they should be taking with respect to their financial plans. They simply have an idea of what their objectives are. It is the advisor's duty to assess risk accurately, and align each client's individual goals with an accurate level of risk (Rattiner, 2005). Both the Australian and U.S. governments have enacted rules and regulations that require planners and advisors to assess their clients' risk tolerance when identifying objectives and needs. As outlined in the U.S. Department of Labor's Pension Protection Act of 2006, understanding risk tolerance is a significant element when giving financial planning advice (Gilliam et al., 2010). The inclusion of the need for accurate risk-assessment in governmental literature and regulation is further evidence of the significance of risk-assessment in the financial planning process.

Assessing an individual's risk profile is not limited to advisors who practice under a fiduciary standard. Any financial advisor who provides advice to clients has various suitability guidelines that he or she must follow. A reasonable determination of an investment's suitability for a client would require, for example, that certain kinds of investment products be recommended only to those individuals who can (and are willing to) tolerate the risks. Further, the potential benefits must justify the amount of risk the individual incurs with the investment selection. Additionally, advisors and brokers are the individuals responsible for determining investment suitability, including prudent risk-assessment. For example, it is not sufficient that a client simply agrees to an investment being suitable. Even if a client affirmatively agrees to

engage in a risky financial decision, the financial representative is under a duty to refrain from making recommendations that are incompatible with the customer's financial profile. That is, the financial representative/advisor must advise the client to do what is most suitable for his/her financial situation, based in part on the client's risk profile. Last, financial advisors and brokers will not satisfy their duty to determine an individual's risk profile by simply disclosing that risk exists (Eccleston, 2013).

Problems with Current Methods of Financial Risk-Assessment

Although the fiduciary standard and proper suitability requirements assume prudent risk-assessment, there is no universally accepted measure for risk-profiling. Therefore, it is difficult to really know if or when this vital step in the financial planning process is fulfilled (Gilliam, Chatterjee, & Grable, 2010). Roszkowski (1998) noted that assessing individuals' tolerance is difficult because risk tolerance is such an ambiguous concept. When making financial risk decisions, literature suggests some distinct elements: (a) the probability of gains, (b) the probability of losses, (c) the amount of potential gain, and (d) the amount of potential loss (MacCrimmon & Wehrung, 1986). To assess risk accurately, the literature suggests that assessments of risk should include items that both clarify the individuals' tolerances for acceptable risk/return trade-offs (Roszkowski et al., 1993) and their risk-propensities outside the realm of personal finance (Rowland, 1996). Roszkowski and Snelbecker (1989) also found that in order to fully gauge individuals' risk-propensity, it is necessary to ask about different risk situations outside of the personal finance landscape. There are numerous instruments available that attempt to measure one's aptitude for risk. The Survey of Consumer Finances (SCF) question is a single-item assessment of risk tolerance that has been used in a number of empirical studies on risk tolerance. Recent versions of the SCF have been conducted every three years by

the National Opinion Research Center at the University of Chicago under the sponsorship of the Federal Reserve Board and other federal agencies (Grable & Lytton, 1999; Kennickell & Starr-McCluer, 1994). The SCF is used to gather data on the financial behaviors of individuals and families. The risk tolerance question reads as follows:

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

- 1. take substantial financial risk expecting to earn substantial returns*
- 2. take above average financial risk expecting to earn above average returns*
- 3. take average financial risk expecting to earn average financial returns*
- 4. not willing to take any financial risk*

Although financial institutions rarely use this exact survey question, they commonly use some variation of the item. These questions often assess clients' financial risk-aversion based on a hypothetical risk/return scenario. These one-question measures do not represent the full spectrum of one's appetite for risk. While these types of assessments help identify an individual's attitude (or tolerance), they do not provide an accurate method of total financial risk-assessment (Grable & Lytton, 2001). Chen and Finke (1996) were among the first to suggest that the SCF measure is a better gauge of an individual's financial situation, as opposed to his/her proxy for risk-aversion. Since then, other researchers have also questioned the use of the single-item measure. Hanna and Chen (1997) found that the SCF question does not necessarily provide pure indicators of individuals' risk preferences. Further, Hanna, Gutter, and Fan (2001) explained that the single-item survey does not link the concept of risk tolerance to economic theory. Additional studies have also found that a single-item measure of risk-assessment cannot possibly accurately assess the complex nature of an individual's risk-proxy (Bonoma &

Schlenker, 1978; Cutler, 1995; Grable & Lytton, 2001; Roszkowski et al., 2005). Simple methods of financial risk-assessment are not capable of addressing all of the aspects of risk that individuals face today. Specifically, it is unsustainable to measure a multidimensional concept like risk-assessment with a one-dimensional tool (Zweig, 2013). Multifaceted approaches of risk-estimation are needed to most accurately gauge an individual's propensity. Grable and Lytton (1999) developed a more comprehensive, 13-item scale that encompasses more than the one-item SCF question. Grable and Lytton's study assessed the validity of the SCF question, and tested it against a more dynamic risk survey. Their results found that the SCF measure was too narrow of a proxy for the broad concept of financial risk tolerance.

Financial advisors/practitioners and academics have traditionally held differing viewpoints on the risk-assessment process. In general, practitioners prefer to rely on simple, quick, efficient questionnaires that give them a general sense of their clients' risk profiles, while satisfying their compliance, regulatory, and/or fiduciary duties. Academics generally support scientific, lengthy surveys to assess individuals' risk profiles. Often, financial advisors and planners rely on heuristic simplification to assess risk. In this profiling procedure, advisors base their judgments of their clients' risk tolerance on factors like age, race, or employment. This practice of evaluating risk is not used officially, nor should it be due to the lack of validity. However, financial advisors have the tendency to be overconfident with their judgments of their clients' risk-assessments. They often feel that their training, experience, and education give them the ability to interpret statements made by clients into accurate assessments of risk (Snelbecker, Roszkowski, & Cutler, 1990). Unfortunately, using this intuition to make assumptions is not always accurate. Further, applying various demographic variables to assess risk, including rules of thumb, is a method that is far from perfect (Roszkowski & Grable, 2005). Another fallacy

associated with current ways financial advisors assess risk is that they confuse risk-assessment variables, making it difficult to accurately quantify an individual's risk score (FPA, 2013). For example, financial advisors often confuse individuals' time horizons with their risk-capacities (ability to withstand risk). Assuming that an individual should not be risk-averse solely based on their age can lead to problems if that individual does not have the capacity to take on risk (Roszkowski & Davey, 2010).

Advisors that rely on their interviewing skills for the assessment of client risk levels also encounter unreliable results. This is even the case when the advisor is a highly skilled professional. Often, even when these experienced advisors utilize questionnaires to assess risk, they do not think it is enough. Advisors feel that current questionnaires do not do an adequate job of gauging their clients' risk-assessments. Advisors and planners feel this way for a number of reasons. First, although it is simple and efficient, some advisors feel that one single questionnaire cannot address all aspects of their clients' risk profile. Other practitioners deem current questionnaires too heavily centered on investment risk, so they are forced to alter the surveys to make them applicable to other aspects of the financial plan (Roszkowski & Davey, 2010). Lastly, some planners conduct additional psychological methods of assessment, such as interviews, in addition to the traditional questionnaire. In these instances, advisors sometimes use the questionnaire as a mere starting point for the risk-evaluation process, supplementing the survey with conversations about risk. One reason advisors feel the need to conduct added interviews is that some questionnaires do not provide enough practical, applicable, and behavioral logic to the assessment process (Droms & Strauss, 2003). This causes advisors to fall into the trap of making subjective, biased assessments of their clients' risk profiles. Additionally, it forces these advisors to spend more time in the risk-assessment process than they would prefer. To combat these

subjective, often misleading judgments of individuals' risk-assessments, a questionnaire is needed for accurate risk-assessment.

Risk questionnaires can be efficient and accessible to financial advisors. However, there is no universally accepted questionnaire that both those in academia and financial service professionals use to assess risk. While the use of a questionnaire to assess risk is simple and straightforward, the extent to which these approaches are successful is questionable (Yook & Everett, 2003). Academic studies that strive towards a universally accepted risk tolerance questionnaire have been unsuccessful to this point (Bouchev, 2004). There could be a number of reasons that the creation and utilization of a standard method has been difficult to adopt. One explanation could be that it has been hard to find a questionnaire that both financial service professionals and academics can agree upon. A major problem with the assessments used by financial advisors is that their respective firms design their own questionnaires in an ad hoc manner. Therefore, the questions used across surveys in the financial planning field differ considerably (Yook & Everett, 2003). Academics have a problem with this inconsistency and lack of predictive validity. Additionally, because the surveys are often put together non-scientifically with little to no validity or reliability, it is difficult to know how well the questionnaires capture an individual's risk landscape (Roskowski & Davey, 2010). Further, these industry-standard questionnaires have the tendency to be too short in length, sometimes being comprised of five questions or less. Historically, practitioners prefer this length of assessment to gain a general, efficient sense of their clients' risk profiles. Another reason that a uniform risk questionnaire has not been adopted is that the risk-assessment process cannot be a one-size-fits-all approach. Because individuals are different, it makes the general assessment of their risk profiles difficult (Roszkowski, 1998). However, without a standardized method to assess one's

risk, a wide range of estimations is more likely, which could lead to inaccurate assessments.

In order to move towards a more accurate risk-estimation process, correcting identifiable imperfections in traditional methods of risk-assessment is necessary. Due to the increase in the number of risk-assessment surveys available, it is becoming increasingly difficult to decide what questions to include, and which surveys should be utilized (Moreschi, 2005b). Traditional surveys tend to focus on quantitative probability and payoff outcomes. They do little in promoting discovery of behavioral tendencies and psychological constructs (Hanna et al., 1998). This could be detrimental to the accuracy of the risk-assessment process. If psychological aspects of risk influence the decision-making process, failure to assess these components may result in an inaccurate plan. Other studies have also found that the traditional methods of risk-assessment focus too much on investment-based issues (Roszkowski et al., 2005).

Although traditional risk questionnaires tend to be simple and straightforward, the extent to which they are successful in capturing an individual's absolute risk profile is questionable. In addition to current methods of assessment being too simple or one-dimensional, another problem is that of who designs the questionnaire or survey. Often, financial services firms design their own questionnaires in an ad hoc fashion. Therefore, the questions included in the surveys differ widely. Because of these deviations, it is possible that an individual's risk profile can be vastly different depending on whose questionnaire is utilized. Yook and Everett (2003) found all of these issues to be the case. Their research found that risk surveys varied widely, and additionally, offered varying explanatory power. Further, the risk questionnaires had low correlations to one another, raising concerns that some questionnaires can adequately gauge an individual's risk, whereas others cannot. This should not be ignored. These findings not only show the variation among current risk-assessment measures, but the results from the study also show the importance

of utilizing a multidimensional school that takes into consideration multiple aspects of an individual's risk profile. Another problem with risk profiles is the way in which their scales are weighted. Specifically, most surveys weight each risk construct equally (Bright & Adams, 2000; Grable, Archuleta, & Nazarinia, 2010; Grable & Lytton, 1999). This assumes that each risk component and each risk question contribute equally to one's overall risk profile score. This may not be a safe assumption, as some aspects of risk may influence an individual's decision more than others. It is not reasonable to assume that each risk-profiling variable equally accounts for the explained variance in an individual's overall risk-profiling score. This study will explore the appropriate weightings given to each risk-profiling variable.

Other research has discovered that psychological aspects, such as feelings and personality type, should be incorporated into risk questionnaires. Adding a behavioral/feelings component to the risk-assessment process, in addition to traditional questions, can make for a more accurate estimate of risk (Magnan & Hinsz, 2005). Other studies have shown that an individual's risk-assessment is not necessarily related to the actual behavior of the individual (Croy, Gerrans, & Speelman, 2010). If an individual's behavior is not taken into consideration in the risk-appraisal process, this kind of result should not be a surprise. In order to most accurately predict financial planning behavior and guide an individual to take the appropriate action, an evaluation including the individual's behavior must be considered. Therefore, assessments that include psychological constructs will be more accurate and effective in financial risk-planning.

Traditional questionnaires sometimes use terminology that is familiar to those in the financial industry, but not to the average individual. As a result, these methods may be misleading, or at the very least, difficult for the average individual to understand (Bouchey, 2004). These surveys may be easier for individuals to comprehend if they were to use simpler,

plainer examples. If individuals better understood the questions that were being asked, their answers may be more accurate. Just because a survey uses sophisticated language and quantitative techniques to assess simulated examples, it does not mean that it is an accurate way to measure risk. These kinds of techniques lose their value if individuals have difficulty interpreting them. Therefore, an additional aspect to consider in assembling a risk tolerance questionnaire is the terminology. Many traditional questionnaires use financial terms and sometimes very elaborate statistics in examples. Individuals may understand questions better, and therefore answer more honestly and accurately, if situational examples and terms that are unrelated to finance could be used when possible (Mellan, 2009). Grable (2000) isolated some variables that affect one's financial risk-assessment, although they were non-financial related. Asking questions in the survey that address these non-financial related issues might be beneficial for individuals who have trouble assessing their risk in financial terms. Further, adding this kind of dimension to the assessment will add to the accuracy of the overall financial risk-calculation. It would be easier for some individuals to quantify their risk attitudes using qualitative, non-finance terms, increasing the probability of an accurate risk-assessment. Many questionnaires assume that the respondent is financially literate, and many are not. One simple misstep can have negative impacts on the assessment. Standard, plain English is one of the ways to deal with this problem (Davey, 2012).

Current Versions of Assessments

Research in financial planning has evolved rapidly over the last two decades. Advisors' understanding of risk, combined with analytical technology, has made it easier to understand various financial situations. Therefore, it has become easier to determine quantitative solutions to a client's financial problem. However, if the quality of the risk-assessment is flawed, the output

of the individual's financial plan will be as well. If the advisor is able to obtain the right information during the risk-assessment process, the entire plan has a better chance of success (Moreschi, 2005a).

Little research has been done to explore how effective the current methods of risk-evaluation, including the questionnaire, are at estimating risk. Roszkowski and Grable (2005) are among the limited group of researchers who have pursued the topic. They found that both advisors and clients are not particularly accurate in risk-estimations. Their research evaluated both financial advisors' and their clients' ability to assess risk. They found that neither financial advisors nor the advisors' clients had a clear understanding of the clients' comfort level with risk. Other studies have been done to test financial advisors' ability to assess their clients' risk tolerance. The majority of the time, and perhaps surprisingly, advisors have not been found to be as accurate as they thought when assessing the risk thresholds of their clients (Torngren & Montgomery, 2004). This may not be the case if more consistent, more accurate methods to assess risk were in place, at the beginning of the financial planning process.

A void in most methods of risk-assessment is the lack of an emotional component. It is assumed that individuals evaluate risk alternatives at a cognitive level (traditional risk models). For example, MPT assumes that individuals are risk-averse, and that they will only incur additional risk for an exact level of expected return. These models are based heavily on the probability and desirability of associated consequences. However, individuals' feelings affect decision-making processes as well. These feelings contribute to the probabilities and outcomes of risk-assessment in a way that is different from what traditional theory would propose (Lowenstein et al., 2001). Therefore, it is important that individuals' emotions (or feelings) be taken into consideration during the risk-assessment process. Means of risk-assessment that utilize

solely cognitive methods are not sufficient. At the very least, individuals' interpretations and assumptions may not be taken into consideration with the current methods of risk-assessment. Further research has been conducted that explores the role of individuals' emotions in the risk decision-making process. Kahneman, Ritov, and Schkade (1999) found that when individuals make decisions, their judgments are often erratic and cannot be understood from the perspective of traditional economic theory. Often, individuals' assessments of risk can be interpreted as "gut feelings" at the time of the decision, described by Kahneman et al. as a "moment of feeling." Sometimes these feelings can be overly positive, which can lead to individuals overestimating their risk-propensities (Nofsinger, 2010). Other times, negative feelings can influence the risk decision, causing individuals to underestimate their risk decisions. The literature shows several instances when risk-aversion flows from the anticipation of negative emotions as well (Bell, 1985; Jeffrey, Onay, & Larrick, 2009; Loomes & Sugden, 1982; Mellers, 2000; Zeelenberg, 1999). Jeffrey et al. (2009) found that when individuals have goals, they will be willing to incur more risk. That is, when financial goals are present, individuals are more likely to forego a more certain option with less return potential for the choice that carries a higher risk/return tradeoff. The results of findings like this are different than the predictions that would come from models rooted in traditional economic theory. Risk needs to be assessed in such a way that individuals' feelings help explain their cognitive processes in the decision-making process. Lowenstein et al. (2001) proposed one method to assist in this process. Their research suggests that there needs to be a distinction between individuals' anticipatory emotions and anticipated emotions—that is, feelings or situations involving risk that have occurred versus those that have not.

Purpose of Study

Information about risk, including each client's risk profile, is crucial to advisors as they

guide their clients. It is important to distinguish risk tolerance from other investor propensities, and to explore relationships among them. Further, this type of exploration is a first step in the construction of a new financial risk-assessment, one that goes beyond risk tolerance, and one that offers financial advisors better tools for serving their clients. A questionnaire is needed that goes beyond risk tolerance and connects multiple aspects of financial risk to an asset allocation model (Pan & Statman, 2012). One of the primary goals of this research was to do just this.

Additionally, this assessment needs to not only be accurate and comprehensive, but also easy and efficient for advisors and clients to use.

The purpose of this study was to extend upon prior literature on financial risk and risk-assessment. The dissertation provided a substantial contribution to the financial risk-assessment literature. Specifically, the study explored the following:

1. *The associations among independent risk-assessment variables.*
2. *The concept that prudent financial risk-assessment goes beyond estimating an individual's risk tolerance.*
3. *The impact that each risk variable has on an individual's overall Comprehensive Risk Profile (CRP).*
4. *A comprehensive method of risk-assessment to estimate an individual's overall risk profile.*
5. *The development of a weighted risk profile score and its assignment to a target asset allocation model.*

This research uncovered which risk-assessment variables impact an individual's overall risk profile the most, and if these risk components should be more heavily weighted in the risk-evaluation process. This work further explored the concept that the risk tolerance variable is not

the only factor in the prudent assessment of one's financial risk. Lastly, the results from this study will help move the financial services industry closer to an accurate, uniform, all-encompassing method of risk-assessment that is easy to implement.

Conceptual Framework

Review of Financial Risk Frameworks

Financial advisors are in the difficult position of providing advice that is rooted in traditional economic theory, but also manage and understand the behaviors of their clients, which are often irrational and not rooted in theory (Finke et al., 2008). An accurate method of risk-assessment, and a thorough understanding of the factors that predict an individual's financial behavior, will make this process more manageable. This may mean that the term "risk tolerance" is no longer used interchangeably with assessing an individual's Comprehensive Risk Profile (CRP). Ultimately, this study produced a comprehensive, accurate method to assess an individual's risk and explain the associations among financial risk-assessment variables.

Many previous studies have utilized the standard Expected Utility (EU) function (e.g., Hanna & Chen, 1997; Yao, Hanna, & Lindamood, 2004). Most of the time, this normative approach fails to explain individuals' risk-taking behavior (Rabin & Thaler, 2001). Additionally, when a normative theory, such as expected utility, is used to assess the nature of individuals' risk profiles, there is little connection between actual behavior and expected utility calculations (Dyckman & Solomon, 1972; Neter & Williams, 1971). Risk studies that utilize EU theory ultimately draw generalizations about individuals' risk attitudes by constructing utility curves to complement them. However, more descriptive theories are needed to resolve the risk-assessment procedure (Hershey, Kunreuther, & Schoemaker, 1982). Further, individuals do not appear to be consistent with their risk decisions across different situations, or methods of assessment

(Schoemaker, 1990). Shefrin and Statman (1985) made similar conclusions. Their research found that, similar to Schoemaker's study, individuals have the tendency to be more willing to take risks when certain losses are anticipated, and more willing to settle for a sure gain when absolute gains are expected. The lack of success in explaining risk behavior from EU functions stems from assumptions that lead to extreme and unrealistic risk-aversions. Further, traditional frameworks do not fully explain the role that personal and environmental factors play in influencing behavior, beyond assuming that individuals should maximize their given expected utility. EU describes how individuals should act in a given situation, but not necessarily how they actually behave (Hanna & Chen, 1997). The factors that shape an individual's risk-taking propensities are not examined as a component of expected utility analyses. Researchers such as Irwin (1993) and Grable, Britt, and Webb (2008) have illustrated the impact of these environmental and predisposing biopsychosocial factors in the risk decision-making process. Grable et al. found that biopsychosocial factors work well in describing and predicting financial risk-taking behavior. They found that rather than relying on one or two objective measures (household income or net worth), biopsychosocial profiling provides financial professionals with a broader picture of their clients' risk behavior.

Other frameworks have been developed to further incorporate psychological factors into the risk decision-making process. Weber's (1997) model for risk decision decomposes the risk preference variable, providing for different ways in which the risk decision may differ, because the individual may perceive the risks and returns to be of similar magnitude in two domains, but likes risk in one domain and dislikes it in another domain. Roszkowski et al. (2005) argued that the avoidance of psychometrics in the risk-assessment process is one of the major problems with current methods of assessment. Psychometrics is the blend of psychology and statistics, and

Roszkowski and his colleagues found that utilizing this approach in the evaluation of risk adds to the validity of the assessment. Additionally, they found that most risk-assessments fail for a number of reasons. First, and most prevalent, many risk questionnaires deal with financial matters that are not really part of the construct of an individual's overall risk-assessment. For example, many risk questionnaires assess risk based on an individual's time horizon. While knowing an individual's time horizon is an important part of the planning process, it is not a risk-based question. This can lead to inaccurate estimates of an individual's true risk level.

Further, perceived risk can be more consistent across the risk decision process than an individual's attitude towards the risk. Therefore, distinguishing between differences in risk perception and risk attitude is vital in establishing a proper risk decision model (Weber, Blais, & Betz, 2002). The traditional EU framework assumes that individuals have a preference for choosing defined choices over probable outcome, which is represented by a utility function. Psychometric methods of risk-assessment do not necessarily correlate with the EU function, providing further evidence that traditional economic frameworks are not the most accurate methods of risk-assessment (Pennings & Smidts, 2000). Additionally, other studies have found that traditional theories, such as modern portfolio theory, are being systematically violated in practice (Baz et al., 1999). In real world decision-making contexts, uncertainty comes from the human inability to access and assess all relevant information, and this causes decision makers to adopt a simplified, altered view of the environment, where risk and uncertainty remain as integral and exterior components. That is, most theoretical frameworks examine a decision maker whose initial situation is riskless. In reality, other risks need to be accounted for in determining a correct analysis. More research needs to be done to address the issue of how to deal with situations where these risks remain out of reach for the decision maker. Baz et al.

coined the term “background risks” for these risks that the individual has little control over. Examples of these types of results are present in the literature. Benartzi and Thaler (1995) found that loss aversion amplifies risk-aversion in standard utility models leading to inconsistent preferences. These inconsistent preferences depend on whether the decision maker takes a short-term or long-term perspective. Specifically, this behavior can be traced back to Kahneman and Tversky’s (1979) work on prospect theory. Because individuals evaluate each choice and a series of risky individual decisions, they generally prefer to not make choices that may lead to losses, even when the expected value of these choices is positive. More recent work suggests that risk-taking behavior is learned by individuals, and is not an exogenous trait of humans or specific utility functions (March, 1996). According to the theory of experiential learning, individuals form preferences based on past choices. This suggests that various experimental learning rules induce long-term preferences for certain choices. This further reiterates the concept that factors outside traditional economic utility/risk frameworks influence individuals’ risk decisions.

Behavioral finance was an unknown field when frameworks like MPT were developed. Today, behavioral finance is an expansion of the neoclassic models of economics and finance. Financial planners have generally accepted psychological attributes for at least part of the financial anomalies that have stricken individuals and the markets over recent years (Olsen, 2010). In recent years, the field has moved past exploring the importance of its existence to how researchers can utilize behavioral finance to better understand the actions of individuals throughout the financial planning process. Olsen’s framework of behavioral finance illustrates the different factors involved in the decision-making process. This paradigm expands on seminal behavioral finance frameworks that incorporate psychology into the risk decision (Kahneman & Tversky, 1979). The model utilizes several constructs in helping to explain, behaviorally, what

goes into the financial decision-making process. The speed of information dissemination, the receptivity of investors, and the network between individuals influence the decision-making process. According to Olsen, frameworks and processes that use the duality of formal logic and the human decision-making process should be the commonly accepted method of assessing decision. Expanding on this logic, a method of risk-assessment that uses a more comprehensive, behavioral approach should be used to coincide with the application of behavioral finance in the financial planning process.

Prior to Olsen's work, Shefrin and Statman (2000) developed a model of behavioral finance as well—a framework they termed the behavioral portfolio theory. In it, they observed that individuals do not view their financial plans, or investments, as a whole. Rather, they picture their investments as distinct layers in a pyramid of assets, where layers are associated with goals, and where attitudes towards risk vary across layers. In this theory, individuals divide their money, or parts of their financial plans, into layers corresponding with many different goals and risk levels.

Loomes and Sugden (1982) developed a framework that focuses on emotional reactions to the risk decision process. Specifically, they formulated decision theories that take into consideration the probability of regret in the risk-assessment process. Their "Regret Theory" is a modified version of the standard EU theory. However, regret theory differs from EU theory in that the expected utility of an option also depends on the regret that one may experience by comparing the outcomes of that option with the outcomes of the rejected option. Their research finds that people experience regret when the outcome of the rejected option would have been better, and rejoice when the outcome of the rejected option would have been worse. The concept is that these emotions are anticipated by the decision maker, and taken into account when

evaluating the different risk options. That is, individuals must accept the fact that either choice will leave them open to the possibility of regret, forcing them to balance the fact that regret will be felt if one option is picked. Taking these options into consideration, regret theory assumes that the tendency is to avoid negative emotions such as regret, and to prefer positive emotions in the risk decision-making process. A significant downside associated with this framework is that it fails to account for other factors that shape an individual's risk profile.

Lampenius and Zickar (2005) developed a model for risk-taking behavior as well. Their model allowed for a classification of the individual through the usage of two additional constructs: speculative risk and risk control. Speculative risk was described as a force that indicates the individual's tendency toward the risk-taking side, whereas risk control as a counterforce indicates the individual's tendency for preferring the risk-averse side. By evaluating both forces, the research provided a framework that allowed the classification of an individual on a risk-taking continuum. Their model, contrary to traditional financial theory, is interactive in that speculative risk, as well as risk control, will be influenced by individuals' previous investment experience and knowledge. In other words, individuals' past experiences will influence the risk decision. The research supporting the model found that individuals with previously high risk control and moderate speculative risk will increase their speculative risk and decrease their risk control, as each are positively reinforced. This finding bucks previous financial theory, where it is generally assumed that individuals are always strictly risk-averse (Sharpe, 1964). The research conducted by Lampenius and Zickar assumes that some individuals will choose the thrill of speculating over the risk-averse selection. Essentially, their model breaks individuals down into four basic groups: (a) conservative investors, (b) risk-managing investors, (c) non-investors, or (d) speculators. Although the model does little to specifically address an

individual's asset allocation or specific financial planning structure, it does illustrate the impact that behavior has on the risk decision.

Few studies have explored the relationship between risk-assessment variables at all, and even fewer have focused on the effects that these variables have on an individual's financial plan. Further, prior research has tended to focus primarily on one or two aspects of risk. Sitkin and Pablo (1992) were among the first to develop a framework that included more than one aspect of an individual's risk behavior. They found it useful to include both risk perception and risk preference as central roles in the risk-assessment process, in addition to risk tolerance. Although their model focused on risk behavior within an organizational setting, their study found that certain characteristics of individuals, as well as their personal characteristics, affect risk decisions.

The problem with many of these frameworks is that, although significant, they are difficult to apply in practice, either through a questionnaire or other evaluation method. Kitces (2006) added to his original paradigm for risk-evaluation by adding risk tolerance/attitude to his framework. In it, he suggested how to apply the paradigm to the assessment process. His model for evaluating a client's risk metric is a composite of risk capacity, risk perception, and risk tolerance/attitude. His three-factor model recognizes that the differences between the items are significant, and are more than "minutia." For example, individuals may have the financial capacity to withstand risk, but they may not have the willingness to do so (risk tolerance/attitude). Kitces alluded to this problem as well. Financial plans and investments of those who have a high risk capacity may hold up fine in the presence of financial shocks and volatility. However, those who are also less risk tolerant would experience extreme angst over those types of situations. Risk perception is a valuable addition to this model. Individuals rarely

change their attitudes about risk itself; they simply change the perception regarding the presence of the risk. Behaviors discussed earlier such as over competence, loss aversion, representativeness, and familiarity all factor into an individual's risk perception. When an individual's risk perception influences the decision by over or under estimating how much risk is present, the individual may make incorrect decisions by misjudging whether a choice is really in line with the other risk-assessment variables. The only way to assess these factors is to utilize the questionnaire that incorporates these different risk-assessment variables.

Cordell (2001) introduced a risk-assessment framework that utilized four separate risk components. These risk components include propensity, attitude, capacity, and knowledge. Cordell used the term "PACK" to refer to these risk-assessment variables, and assigned the name "RiskPACK" to his framework for risk assessment. By evaluating four distinct aspects of risk, Cordell envisioned a more accurate risk-assessment process, as well as a better understanding of an individual's needs and behaviors. The RiskPACK model suggests that an individual's overall risk should be separated into these four risk-assessment variables to gain a better, more accurate understanding of their complete risk assessment. This study will extend upon the work of Cordell by exploring the associations between these kinds of risk-profiling variables, and identifying appropriate weightings to allocate to each variable in the development of a scale.

Grable (2008) extended upon Cordell's framework by presenting a single risk profile score for individuals. The model took an individual's risk tolerance, risk capacity, and time horizon into consideration in the assessment. While risk capacity and risk tolerance are extremely important factors in the risk-assessment process, further exploration is needed to learn about how additional factors affect the risk decision. Further, although time horizon is an extremely vital part of the financial planning process, and it is often included as a sub-component

of an individual's risk capacity, it is not necessarily an accurate measure of one's risk (Roszkowski et al., 2005). Other studies have also built upon Cordell's constructs. Schooley and Worden (2003) explored the risk tolerance and investment behavior of those in Generation X. They utilized the RiskPACK framework to guide their study, and found that it was effective in evaluating individuals' risk. Jia, Dyer, and Butler (1999) considered the risk decision as a function of risk perception and risk tolerance. Specifically, they conceptualized the following:

$$\text{Risk Taking} = f(\text{Perceived Return}, \text{Risk Attitude}, \text{Risk Perception}).$$

Theoretical Framework to Guide This Study

A most promising conceptualization was introduced by Coleman (2007). Coleman's model for risk decisions incorporates several behaviors to the risk-assessment process. His framework takes into account risk perception, and individuals' reference levels for risk, mental accounting, outcomes of past decisions, and the effects of outside influences (e.g., experts' opinions). The inclusion of these kinds of variables makes a considerable impact on the risk decision-making process, especially when traditional models have ignored qualitative, behavioral biases. An individual's risk-taking is influenced by a combination of personal, environmental, situational, and definitional aspects of the decision. Using these factors as a basis for the framework, Coleman developed the model that can be expected to drive the decision of an individual who faces financial risk choice. His model is shown in Figure 1.1.

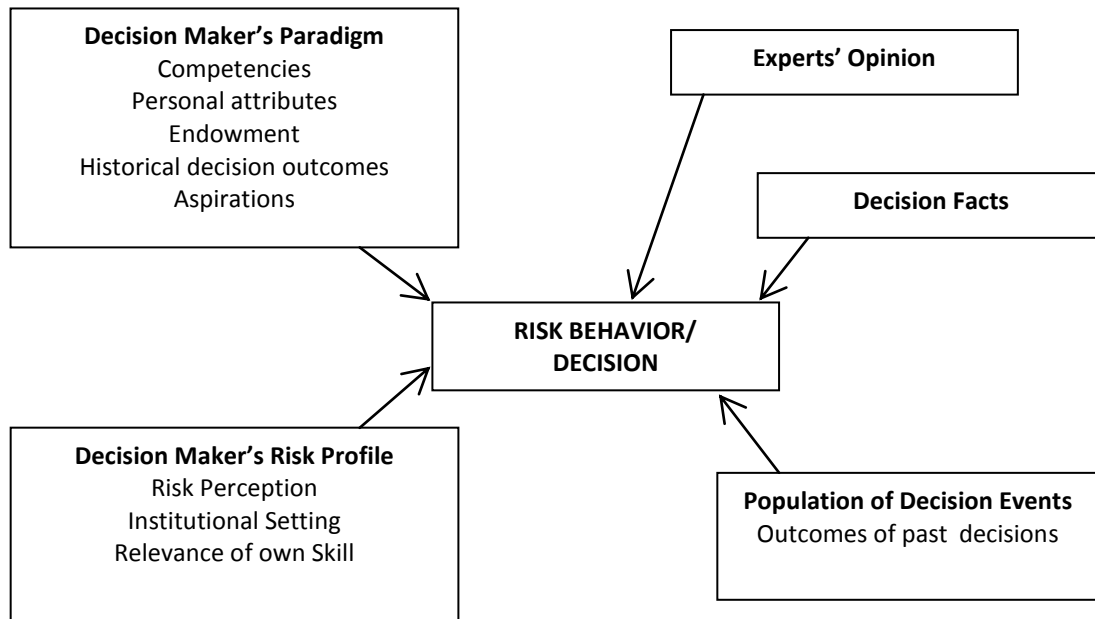


Figure 1.1 Coleman's (2007) Risk Decision Model

Coleman's framework will serve as the conceptual model for this study. While not every aspect of the model will be explored in detail, Coleman's Decision Maker's Risk Profile will guide the empirical analysis for this study. Specifically, constructs generally thought to be associated with the risk-assessment process will be tested to determine if a risk profile can be developed for individuals. An expert panel will then apply this risk profile to a target asset allocation model.

As conceptualized in this study, an individual's risk profile is a combination of a number of risk-profiling variables. This study will focus on Coleman's Decision Maker's Risk Profile by adapting Hanna, Waller, and Finke's (2008) conceptual model for risk decisions in the development of a Comprehensive Risk Profile (CRP) measure. Hanna et al. took the adoption of emotions and feelings in risk-assessment a step further by drafting a conceptual model for risk decisions that takes these factors into consideration. As seen in Figure 1.2, risk tolerance (one's willingness to accept risk) is not the only factor that should go into the risk decision. Hanna et al.

determined that risk capacity, expectations, and feelings about volatility should also be considered in the risk-assessment process. Although a scale was not developed as a result of their research, and the relationship between the variables was not explored, their model and research does suggest that there is more than one component influencing the risk decision. This research will extend Hanna et al.'s research by determining an individual's CRP as a weighted-scale, which can further be utilized to allocate investment assets appropriately. Additionally, the study will provide practitioners and academics with insight as to how related these risk-assessment variables are to one another.

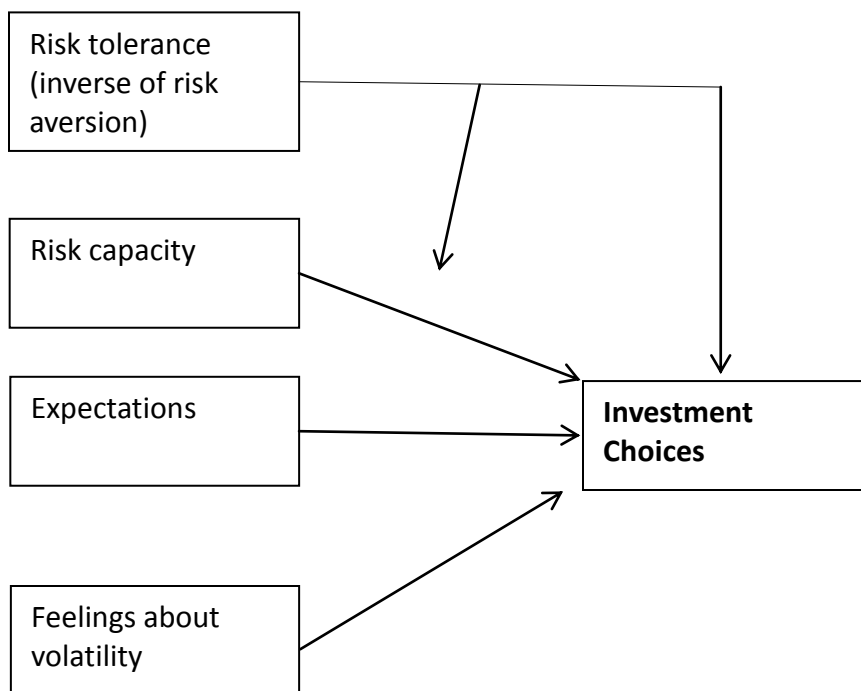


Figure 1.2 Hanna et al.'s (2008) Conceptual Model of Investment Choices Involving Risk

The Hanna et al. (2008) framework fits well within Coleman's (2007) conceptualization. Both models attempt to explain risk-taking behavior. Within Coleman's framework, there are a number of factors shown to influence decisions. The most important factor in conceptualizing

this study is the “Decision Maker’s Risk Profile.” On the other hand, the framework developed by Hanna and his associates shows how the Decision Maker’s Risk Profile can be operationalized. This operationalization is of interest in this dissertation. That is, this project added to Hanna et al.’s framework, which is within the larger theoretical umbrella of Coleman’s model. Together, the two frameworks served as guides to the empirical model for this study. This study added to the prior frameworks by including more constructs (ex. Risk need, risk knowledge, risk composure) to the risk decision-making process, exploring the relationships among the risk constructs, and assessing the impact each risk variable has on an individual’s overall risk profile.

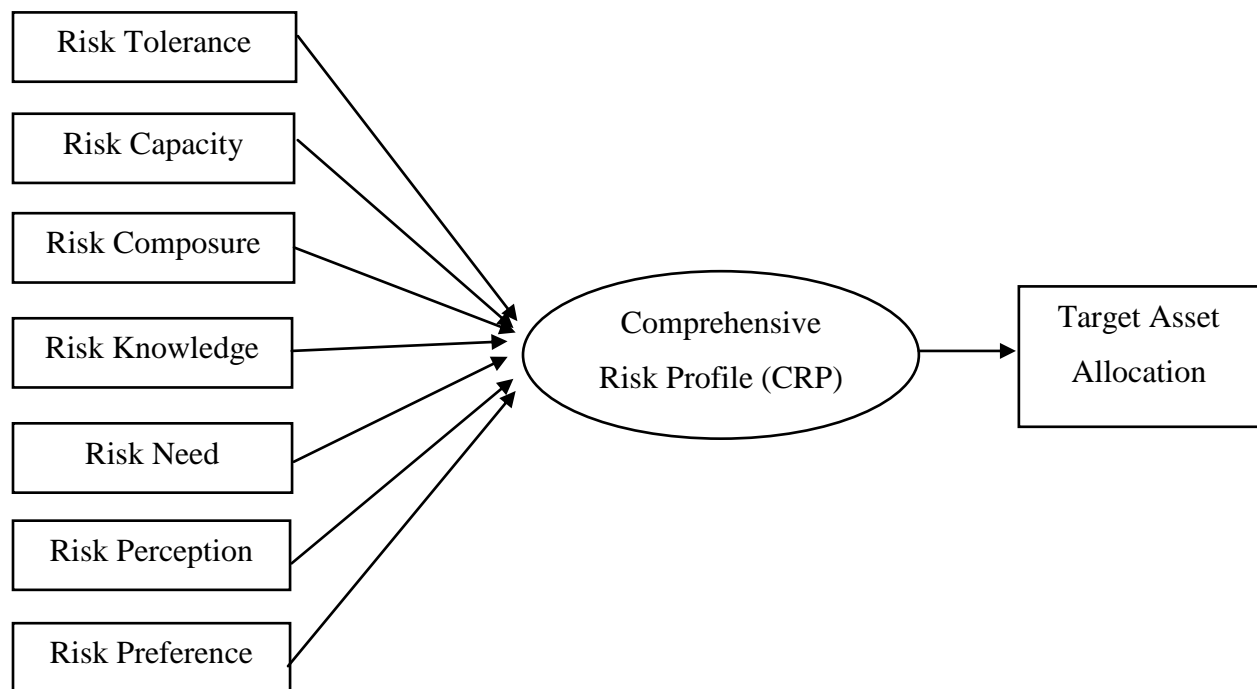


Figure 1.3 The Empirical (Operationalized) Model for the Comprehensive Risk Profile

Definitions of Terms

For the purposes of this study, the following definitions were used:

Risk Tolerance (sometimes referred to as risk attitude in the literature). An individual's willingness to accept risk (Dalton & Dalton, 2004). Somewhat misleading, sometimes the term risk tolerance is used interchangeably with an individual's CRP, or other risk-profiling variables. *Example of risk tolerance: An individual is willing to invest a large portion of his/her wealth into stocks.*

Risk Capacity. An individual's ability to withstand risk (Samuelson, 1969). *Example of risk capacity: Based on an individual's large amount of insurance, and significant amount of money in savings, he or she is able to withstand a large degree of financial risk.*

Risk Perception. An individual's subjective view of risk (Sitkin & Pablo, 1992). *Example of risk perception: One individual may view risk as an opportunity to invest, whereas another person may view the same risk as an almost-certain loss.*

Risk Preference. An individual's choice to engage in risk (Sharpe, 1964; Kitces, 2006). *Example of risk preference: An individual prefers to invest in bonds rather than in stocks.*

Risk Composure (sometimes referred to as risk propensity in the literature). How an individual actually behaves in the presence of risk (Cordell, 2001). *Example of risk composure: Someone who has a high risk composure would be an individual who chooses to add to his/her investments that have declined in value, whereas someone with a low risk composure is an individual who has the tendency to sell his/her investments in periods of decline.*

Risk Knowledge. An individual's understanding, or aptitude, of risk (Cordell, 2001). *Example of risk knowledge: An individual's understanding of the relationship between interest rates and bond prices.*

Risk Need. The amount of risk an individual must take in order to accomplish a given financial goal (Grable & Lytton, 1999). *Example of risk need: An individual who has not saved*

enough for retirement may have a high risk need in trying to accomplish the goal.

Asset Allocation. The process of determining the appropriate mix of assets to hold in an investment portfolio. It involves dividing a portfolio among different asset classes, such as stocks, bonds, and cash (SEC, 2013).

Risk Aversion. An individual's natural preference to avoid a risky decision, when given a choice.

Behavioral Finance. The study of how emotions and cognitive biases affect a financial decision (Nofsinger, 2010).

Risk. In general, the potential for loss.

Comprehensive Risk Profile (CRP). The comprehensive evaluation of an individual's complete financial risk-assessment.

Comprehensive Risk Profile (CRP) Score. The weighted value placed on an individual's risk profile based on the evaluation of the CRP.

Risk-Assessment. The process by which an individual's Comprehensive Risk Profile (CRP) is evaluated.

Delimitations

There are some delimitations associated with this study. A quantitative cross-sectional analysis was utilized. Although there are a number of risk-profiling variables, for the purposes of this study, the seven risk-profiling variables defined above were used. The purpose of this study was to explore the psychosocial factors associated with risk-assessment, not demographic factors. As a result, demographic variables (race, gender, marital status) were intentionally omitted from the study. Further, the sample for this study was relatively small (n=321), which may result in limited generalizability. However, this study was meant to be exploratory in nature,

so at this time, the power of the result is not a significant concern.

Summary and Organization of the Remainder of the Dissertation

This chapter has provided an overview for this study. Risk-assessment is one of the instrumental steps in the financial planning process. However, to date, there are numerous problems with the way financial risk is assessed. This has many implications—in practice, in academics, and in regulatory oversight. The first chapter of this dissertation has reviewed the reasons that risk-assessment is vital to the financial planning process, the problems with current methods of assessments, the specific purposes of the study, the definitions of terms used throughout the research, and a review of the conceptual frameworks used to guide the study.

Chapter 2 will provide further review of the literature involving financial risk-assessment. Specifically, the review of prior research will expand upon the introductory material in Chapter 1, and further develop the need for this study based on the literature. Chapter 3 provides a review of the methodology that will be utilized. Specifically, details on the study's sample and methods of data analysis will be reviewed. Chapter 4 will describe the results from the data analysis. Finally, Chapter 5 will discuss the outcomes of the study, an interpretation of the results, and the implications and limitations of the research.

Chapter 2 - Literature Review

The Risk-Assessment Process and Practitioner Responsibility

Although an extremely important emphasis is put on risk-assessment during the financial planning process, the process is in its infancy, and it is a frequently misunderstood concept (Finke et al., 2008). Unfortunately, practitioners may not do as accurate of a job as they think in assessing their clients' risk. Roszkowski and Grable (2005) found this to be the case. Misinterpreting an individual's risk-assessment can cause major problems in the financial planning process. First, a client's financial satisfaction or goals may not be fully realized if the risk-assessment procedure is flawed. Although the role of risk-assessment is as important to the financial planning process as it has ever been, and there seem to be increasing regulatory elements regarding the process, there is no uniform method for determining an individual's risk profile (Hanna et al., 2008). Second, advisors may be held responsible, from a fiduciary and suitability standpoint, if they fail to accurately assess their clients' risk levels (Trone, 2009). Today, the thorough examination of a client's needs is not just a recommendation, but it is also a requirement. Both the Securities and Exchange Commission (SEC) and the Department of Labor are hiring more auditors (Trone, 2011). Advisors and planners will need to illustrate how they arrive at their decisions for clients, and how these processes meet new standards. Legal cases that explore the client-fiduciary relationship have put financial advisors and planners under even more scrutiny to be accountable for the advice they give to their clients (Lamm-Tennant, 1994). Roszkowski, Davey, and Grable (2005) noted that financial advisors and planners will be held responsible for misrepresenting clients' risk profiles in the future if accurate assessments are not conducted. The legal ramifications of not upholding the fiduciary standard is present outside of the United States as well. In the case of *Ali vs. Hartley Poynton* in 2002, the Australian Victorian

Supreme Court ruled that financial planners have a fiduciary responsibility in the construction of appropriate plans for their clients, based on the clients' needs, goals, and risk-assessment (Van de Venter & Michayluk, 2007).

Roszkowski and Grable (2005) explained that one of the core obligations of financial planners when providing advice is that they fully understand the attitudes, values, and behavior regarding the needs of their clients, including their risk profile. Another potential bias in the risk-assessment process is financial advisors' inability to take the procedure seriously, and to complete the process free of "rule of thumb" assessments and traditional prejudices (Roszkowski et al. 1993). Studies have shown that problems associated with current methods of risk-assessment include a financial planner's bias to "give only lip service to analyzing one's level of financial risk" (Roszkowski, 1995, p. RT 1). Roszkowski et al. (1993) found that an advisor's assessment of a client's risk tolerance was largely based on demographics like gender, age, profession, income, race, and education. Although financial advisors have a fiduciary responsibility to fully understand their clients' risk level, there is an alarming consensus that these kinds of demographics are adequate in assessing risk (Grable & Lytton, 1998). It is troubling that these demographic biases can have such a strong influence on the risk-assessment process. While it is generally accepted that demographic variables can have an impact on individuals' risk profiles, blanket subjective biases should not be used to adequately assess risk (Roszkowski et al., 1993). ~~Whereas~~ general demographic information is useful to know, advisors have a fiduciary responsibility to know each one of their clients' risk appetite. Biased judgments that apply to the masses do not suffice in practice. The advisor must assess each client's risk profile individually to fully understand the individual. This is similar to the medical profession, in which a physician cannot just assume a patient has diabetes just because he or she

fits a certain generalization. An individual evaluation must be done to determine the health, and ultimately the diagnosis, of the person. Financial advisors ought to approach risk-assessment in the same manner. They cannot assume that because an individual fits a certain profile, little to no further risk-evaluation needs to be done. Each individual is different, regardless of what generalities are present regarding race, gender, age, or any other demographic factor.

While it is applicable for policy makers and other bodies to know the demographics behind risk-profiling, generalizing each individual poses a problem for financial planners. The routine practice of basing an individual's risk profile on the life-cycle theory is inadequate (Van de Venter & Michayluk, 2007). The theory, which suggests that individuals' financial plans should become more conservative as they age, relies on one factor in determining a financial plan. If advisors and planners were to rely on one variable to construct a financial plan, they would ignore other factors that are critical to the planning process, such as an individual's risk perception and subjective risk tolerances. These other factors, in addition to goals, needs, and other risk constructs, are not just important components of the financial planning process, but they are also requirements. Too often, financial advisors use these generalized, biased, subjective judgments in lieu of a thorough examination of the individual's risk profile (Hanna et al., 2008; Roszkowski & Grable, 2005; Van de Venter & Michayluk, 2007). Many financial advisors are held to a standard far deeper than the traditional "know your client" standard. For Certified Financial Planners (CFPs), Certified Investment Management Analysts (CIMAs), or any practitioner who is viewed by their client as a fiduciary, a deeper set of client assessment standards are applicable. Fiduciaries are always presumed to act in the best interest of their clients. In order to do so, a thoughtful, thorough examination of the client's risk profile must be conducted.

Regardless of the financial strategy or products a financial planner recommends, the risk-assessment is critical to both the financial planning process and client due diligence. The assessment of one's risk affects the design, the recommendation, the construction, and ultimately, the success of a financial plan. However, there is currently no uniform method that both those in academia and financial service professionals use to assess risk tolerance (Yook & Everett, 2003). Additionally, little research has been done to measure the effectiveness of current risk-assessment techniques. Therefore, it is unclear if current methods of risk-assessment work effectively. This is troubling for a number of reasons. Since risk-assessment is conducted at the beginning of the financial planning process, it is imperative that it is done accurately. If this step in the process falters, the rest of the financial planning process may be inaccurate, leading to a failed financial plan. At the very least, incorrectly estimating a client's risk profile could result in unmet expectations and decreased financial satisfaction in the event of negative outcomes. Additionally, since there is no single risk-assessment method accepted by the financial services industry and academia, measures of risk can be very subjective. That is, one advisor's assessment of a client's risk profile could be very different from another advisor's evaluation due to responses from varying assessment techniques (Yook & Everett, 2003). Further, it is unclear which, if any, of these methods of evaluation are accurate in assessing risk.

There are prevalent problems with current methods of risk-assessment, and the way risk is currently viewed. First, risk is not a one-dimensional attitude (Cutler, 1995). However, many of the surveys currently used to assess risk are just that. An individual's attitude is a complex, multidimensional characteristic, and assessments should take this into consideration. Otherwise, one-dimensional approaches will be incomplete and misleading. Second, individuals generally feel that they have an accurate sense of the financial risk they are willing to/should take. This is

not always the case. In addition to Cutler's research, other studies have found similar findings (e.g., Roszkowski & Grable, 2005). Additionally, "rule of thumb" assessments blur the accurate assessment of financial risk (e.g., older individuals must take on more risk with their finances). These kinds of blanket assessments that are generalized for entire populations can be inaccurate. A careful evaluation must be done on each individual to determine an accurate risk profile.

The financial crisis of 2008 exposed not only the shortcomings of the financial system, but also the tools used by financial advisors to assess risk and guide investors (Pan & Statman, 2012). Typical questionnaires are deficient for a number of reasons. First, existing financial risk-assessment questionnaires generally offer no clear linkage between risk scores derived from questionnaires and portfolio asset allocations. Other tools provide linkages based on opaque rules of thumb (Pan & Statman, 2012; Roszkowski et al., 1993). Additionally, individual assessment of risk varies depending on current circumstances as well as emotions. Failure to recognize behavior in the risk-assessment process is likely to result in disappointment, or financial dissatisfaction. Finally, investor propensities, in addition to risk tolerance, matter to advisors when they work with their clients on establishing accurate risk parameters. Therefore, the inclusion of other aspects of risk and behaviors is imperative in the financial risk-assessment process. Neglecting to include behavior in the risk-assessment process can lead to regret and, ultimately, disappointment in the financial advisor-client relationship (Pan & Statman, 2012).

The Risk Questionnaire

The most common method of assessing an individual's risk is the questionnaire. Although there have been attempts to dispel this method as the most appropriate vehicle to assess risk, an individual's risk can be measured accurately with the right tool (Roszkowski et al., 2005). Traditional risk-assessments (such as the Survey of Financial Risk Tolerance, or SORT)

tend to not be very client-friendly in the structure of their questions. For example, these tools use many finance industry-specific terms, and focus on various quantitative probability and payoff outcomes. These questionnaires may not make sense to an individual who is unfamiliar with financial terms or expressing their needs quantitatively. On the other end of the risk-assessment spectrum, there are other surveys that focus too heavily on subjective or emotional responses to risk. Both subjective (e.g., the individual's point of view or opinion) and objective (factual) factors must be taken into consideration when evaluating risk (Adkins, 1997). Generally, questionnaires have been found to be too brief, and they include too many poor questions (Roszkowski et al., 2005). There is also the issue of why financial advisors assess their clients' risk in the first place. Is it done to better understand the needs and situations of their clients, in an attempt to adhere to the fiduciary standard? Or, do advisors simply use risk-profiling as a way to provide legal cover? Relying on the results of a superficial risk questionnaire may cover the advisor in the case of a lawsuit, or arbitration, but it does not ensure an accurate, adequate measure of risk-assessment for the client (Cordell, 2001). This concept should not be overlooked. That is, many of the questionnaires developed for financial service practitioners are used to cover the financial services firm, or advisor, from a compliance standpoint. However, the assessment may do very little to help truly understand the risk propensities of a client. More needs to be done in order to both fully and accurately understand an individual's risk parameters and suitability, while also providing legal coverage of the fiduciary rule for the institution.

Risk as a Multidimensional Construct

Jackson, Hourany, and Vidmar (2006) were among the first to present risk in a multidimensional format. They contended that one's risk-assessment is made up of four components: (a) financial, (b) physical, (c) social, and (d) ethical. Additionally, they found that

there is consistency in decision-making across each of these dimensions. One of the major problems with current measures of risk-assessment, and one of the main focuses of this study, is that risk definitions are used interchangeably. Other research has also found that multidimensional assessment measures are a more accurate way to profile for risk. Constructs such as risk tolerance, risk capacity, and risk preference should not be used to mean the same thing. What many advisors and individuals do not understand is that an individual's risk profile is actually comprised of many parts, which can sometimes result in contradictory indications about the most appropriate risk-assessment (Kitces, 2006). Kitces found that while risk capacity is all about the financial aspects of the individual's ability to sustain risk, risk tolerance measures the individual's abstract ability to handle risk emotionally, or behaviorally. Since risk tolerance evaluates an individual's willingness to take on the risk, the variable has absolutely nothing to do with the risk capacity—whether the individual has considerable assets or limited assets on the balance sheet. Kitces recommended taking into consideration both risk capacity as well as risk tolerance in the financial risk-assessment process. In his model, the combination of an individual's financial risk capacity and emotional risk tolerance form the overall profile to determine appropriate financial solutions. One of the most glaring reasons for the use of a multidimensional assessment tool is the perceived difference between risk-assessment variables. For example, Kitces explained that there is a perceived difference between risk tolerance and risk capacity, often contradicting each other. Individuals often have strong savings habits and/or favorable financial situations, possibly due to the result of an inheritance. However, these individuals can still be very conservative when it comes to how much risk they are willing to take with respect to their financial plan. In this scenario, an individual's responses might be very low on items that address risk tolerance, but very high on the items that address risk capacity. If a

survey relies on just one aspect of risk (i.e., either risk tolerance or risk capacity), the accuracy of the assessment will be inadequate. A useful model that allows for a valid risk-assessment is one that utilizes various aspects of risk-evaluation to form a more complete picture of an individual's risk profile. For the purpose of this study, seven independent risk-assessment variables were used. These factors included: risk tolerance/attitude, risk capacity, risk perception, risk preference, risk propensity/composure, risk need, and risk knowledge. The definitions for each risk variable, as adopted from earlier studies and/or definitions, will be discussed below.

Risk Tolerance

Risk tolerance is a vital component to the risk-assessment process. In making recommendations, a financial advisor needs to consider how much risk a client is willing to take (Roszkowski & Snelbecker, 1989). When offered a choice between a relatively small but certain payoff and one that is probable but not certain, most individuals will choose the likely payoff over the unlikely, but potentially larger, payoff. This is because individuals are less willing to pass up certainty with respect to financial risk. The textbook definition of risk tolerance (Dalton & Dalton, 2004, p. 898) is the following: “An estimate of the level of risk an investor is willing to accept in his or her investment portfolio.”

It is not unusual for individuals to have unrealistic expectations about the likelihood, or amount, of return, given the amount of risk they are willing to assume. The SCF risk tolerance question (see Chapter 1) asks respondents if they are willing to take greater risk to achieve greater returns. While the SCF item has been a popular measure of risk-assessment, it has received a great deal of criticism in the literature about its ability to gauge risk on a comprehensive basis. Chen and Finke (1996) were among the first to suggest that the SCF measure might be a better indicator of an individual's “financial situation,” rather than “a good

proxy for risk aversion” (p. 94). Hanna and Chen (1997) also questioned the use of the SCF measure. Their research noted that it does not reveal pure risk preferences. Additionally, Hanna, Gutter, and Fan (2001) explained that the single-item SCF question was not linked to the concept of risk tolerance in economic theory. Further, Grable and Lytton (2001) cautioned researchers and practitioners to use the SCF item with care. They were concerned that using the results from the SCF question beyond the scope of investment risk may lead to inaccurate assessments. Follow up studies found similar results (Gilliam et al., 2010).

Individuals’ willingness to accept risk may not be the only facet of risk. It is common to see the term “risk tolerance” used in the literature to describe individuals’ feelings that are not truly willingness to take on risk. These composite risk measures include individual behavior or emotions, but they are not exclusive to one’s risk tolerance, or willingness to accept risk (Lindamood et al., 2007). Other studies have added to the concept of risk tolerance, as a standalone measure of financial risk. Hallahan, Faff, and McKenzie (2004) described risk tolerance in a comparable way. They stated that individuals’ risk attitudes are comprehensive, and often factor in current feelings and emotions. Other studies have reported similar results (e.g., Yao, Hanna, & Lindamood, 2004). These risk attitudes can vary depending on prior outcomes (Post, Van Den Assem, Baltussen, & Thaler, 2008). Individuals who have recently experienced bad luck may become less willing to accept risk. Conversely, a string of positive results may increase an individual’s risk tolerance. A conceptual model of an individual’s willingness to take financial risk was developed by Yao et al. (2004). If risk tolerance changes in the way that their conceptualization indicates, there is a chance that an individual’s willingness to take risk will be inaccurate or inconsistent. Therefore, although risk tolerance is an integral part of the risk-assessment process, it should not be used interchangeably with other measures of

risk assessment. That is, the literature suggests that financial advisors and researchers should avoid using risk tolerance as a blanket assessment for an individual's overall risk when they are discussing a composite measure (Lindamood et al., 2007).

Although the term risk tolerance is often used to describe someone's holistic maximum level of acceptable risk, the term was utilized much more specifically in this study. This research adopted Cordell's (2001) definition as follows: financial risk tolerance is the maximum amount of uncertainty that an individual is willing to accept when making a financial decision.

Risk Capacity

Samuelson (1969) was among the first to recognize the significance of risk capacity, or one's ability to withstand risk. There are certain elements, objective factors, of an individual's financial plan that have an impact on the risk-assessment process. Wealth, future wealth, time horizon, and amount of insurance coverage are examples of these factors. These are some of the main components of risk capacity. As opposed to subjective choices that individuals can make with respect to a risk decision, risk capacity items are objective in that the responses tend to be black and white. They are factual by nature. For example, individuals' net worth is objective. There is also an objective response for how long an individual has until retirement, or the amount of debt he or she holds. These factors are vital to the risk-assessment process because they provide elements of certainty. Further, variables like age (or length of time until retirement) and income are commonly seen in the literature as determinants of risk-assessment, and need to somehow be accounted for in the assessment process (Hanna & Chen, 1997; Rajarajan, 2003). Including these objective variables in a construct such as risk capacity allows practitioners to gauge risk objectively. Hanna and Chen (1997) proposed that risk capacity can be measured by including both time horizon and net worth as the main determinants. To illustrate, they suggested

that individuals with a substantial net worth, as well as a long time horizon, would be classified as having a very high risk capacity. The application of risk capacity is theoretically grounded in the life-cycle hypothesis (Modigliani, 1963). This framework suggests that acceptable risk can be keyed to an individual's life cycle, to a degree (personal preferences are still a factor).

Specifically, younger individuals have the capacity to withstand more financial volatility, as they have more time remaining in their lives to recoup losses. Malkiel (1990) also suggested that an individual's capacity for risk decreases with age. His logic also implies that as individuals grow older, they have less time to recoup financial loss. Therefore, they need to take less risk with respect to their investments and financial plans.

Future time perspective has received considerable attention in the literature. It is a measure of the extent to which individuals focus on the future, rather than the present or past, when making financial decisions (Jacobs-Lawson & Hershey, 2005). Trostel and Taylor (2001) developed an economic-based framework for time preference. They proposed that individuals place a lower marginal value on consumption in the future because the expected marginal ability to enjoy the consumption is lower in the future. This discounting occurs because the marginal utility of individuals' consumption is eventually declining. The authors related the theory back to the field of personal financial planning by using the framework to explain why so few individuals buy annuities. They suggested that individuals' time preferences weigh heavily on the decision. According to time preference theory, individuals' consumption in old age is assumed to yield little utility. Thus, the preference to enjoy the benefits of the annuity is small. The life-cycle hypothesis suggests similar expectations (Ando & Modigliani, 1966). The effects of the theory of time preference are far-reaching as it relates to the risk composure construct. Individuals who do not perceive their financial plan as increasing their marginal utility may

abandon their strategy quicker than those who do expect increasing utility. These individuals who choose to veer off course would be said to have a lower risk composure.

Those who can accurately assess the passage of time can be more effective in their ability to tolerate risk. Patton, Stanford, and Barratt (1983) found that impulsivity was associated with time preference. Specifically, individuals who are more impulsive are less likely to delay a decision. That is, they act on their impulses. Gerber (1987) explained that this was largely due to their internal clock, or time preference, moving much faster than the internal clock of those who are not impulsive. Those who are less impulsive would probably have higher levels of risk capacity. One common relationship is the link between individuals' wealth and time preferences. As individuals' wealth increases, so does their patience for present goods (Block, Barnett, & Salerno, 2006). Additionally, those with higher income levels are less impulsive with their demand for goods (Hoppe, 1993). This could be interpreted to mean that when individuals have enough income and wealth to consume the optimal amounts of goods, they have less of an urgency to consume future goods (knowing that they will have a decrease in marginal utility).

Prior literature illustrates the differences between individuals' tolerance for risk and their capacity for it (Adkins, 1997; Cordell, 2001; Kitces, 2006). Risk capacity refers to an individual's ability to incur risks, including liabilities and other contractual commitments. Adkins suggested that one of the reasons risk capacity exists on a different plane than risk tolerance is because of its objectivity. That is, risk tolerance (and several others of the risk constructs) is subjective in that the individual offers an opinion, often emotional, with respect to the risk variable. Risk capacity can be measured factually or objectively. These objective measures, when combined with subjective assessments, may lead to a more accurate assessment process. At the very least, the risk-assessment process should not be entirely subjective or

objective, but rather a combination of the approaches so that financial advisors do not just tailor a plan towards what a client wants (subjectively). Instead, they should also develop a strategy that incorporates what the individual needs objectively. Hanna et al. (2001) also found that learning about both an individual's subjective and objective choices better prepares an advisor to make informed, accurate recommendations. Other studies have also found that prudent risk-assessment investigates both subjective and objective measures (Hanna & Chen, 1997).

Insurance coverage is a vital part of risk capacity assessment, though it is often ignored in practice (Cordell, 2002). Other aspects of an individual's risk capacity could be factors such as income and net worth. For the purpose of this study, risk capacity was defined as one's financial ability to withstand loss or a risk (Cordell, 2001), and was assessed using adequacy measures related to insurance, net worth, time horizon, and savings. Risk capacity was measured and evaluated using benchmarks advocated by Cordell (2002), Grable (2008), and Kitces (2006).

Risk Perception

Risk capacity is not the only construct that is used interchangeably with risk tolerance. Sitkin and Pablo (1992) found that risk perception, defined as how individuals subjectively view (or perceive) risk, is a key determinant in assessing financial behavior. They found that variables such as risk perception should not be used interchangeably with the term risk tolerance, which has long been understood as one's willingness to take risk. Their research explained that an individual's perception of risk can drive the risk-taking decision just as much as their willingness to take risk (tolerance). Weber, Blais, and Betz (2002) also found that individuals' risk perception is different than their risk tolerance. Similarly, Roszkowski and Davey (2010) explored the impact that risk perception has on the decision-making process. They claimed that individuals' tolerance for risk did not change much throughout the 2008 economic crisis. Instead,

they proposed that individuals' risk perception had changed. That is, individuals perceived risk differently after the 2008 economic crisis than they did prior to that time.

Although traditional methods of risk-assessment assume that individuals act rationally, there are many biases that can lead individuals to act seemingly irrationally. By allowing psychological biases and emotions to affect the financial decision-making process, individuals can do serious harm to their wealth (Baker & Nofsinger, 2002). Kahneman and Riepe (1998) noted that individuals who are prone to behavioral biases will take risks that they do not realize are risks, and consequently may blame themselves or others when the outcomes are poor. If financial advisors can understand these biases, they can take action to help reduce their effects on financial planning decisions, possibly improving results. A potential way that advisors can better understand these behaviors is to account for them in the risk-assessment process.

There are a number of reasons individuals are influenced by emotion, including various biases many individuals exhibit (Nofsinger, 2005). Therefore, it makes sense to include behavioral components, in addition to traditional risk-assessment techniques, to account for their presence in individuals' thought processes. Risk-assessment is more than just a quantitative concept. Therefore, feelings and emotions should be considered when estimating risk. These emotional qualities and behavioral reactions are needed in order to understand someone's estimated reactions to real financial events (Magnan & Hinsz, 2005). A questionnaire usually assumes that all individuals *perceive* risk the same way. That is, each individual views various risky financial outcomes and events the same way. To the extent that this assumption is false, it is important for questionnaires to help decipher which events are deemed risky to each respondent (Mellan, 2009). For example, some individuals may consider inadequate insurance coverage as a risky event, while others may not. One person may be terrified of not leaving any

money to their heirs, while another may not be fearful of leaving little or no legacy behind. These considerations could be taken into account on questionnaires, recognizing that each respondent will perceive risk differently. Knowing how each client perceives various risky outcomes, or worst-case scenarios, advisors may be better able to prepare clients and set expectations for risk. This kind of education should be ongoing, given that various events can change an individual's risk perception. One's financial plan does not necessarily need to change just because an unforeseen or unfortunate event transpires. However, because one's perception of risk may have been altered, he or she must be educated so that proper expectations can still be met. Financial advisors who are aware of the effects of risk perception would be able to consult with their clients about how the trait influences the decision-making process. That is, financial advisors and planners should work with their clients to help them understand the difference between changes in their risk perception of a certain aspect of the financial plan (an investment) and the actual variations in the inherent risk. This will not only better educate clients, but also assist in setting proper expectations.

For example, although wealthy and less affluent individuals may have the same risk tolerance, they will likely have differences in risk perception (Pan & Statman, 2012). Therefore, the failure to distinguish between the two risk-assessment variables can bias the overall evaluation of risk. There is a fair amount of literature on the subject of distinguishing the differences between risk tolerance and risk perception (see also Roszkowski & Davey, 2010; Gilliam et al., 2010; Horvath & Zuckerman, 1993; Weber & Milliman, 1997). One of the reasons that risk perception differs from risk tolerance is that risk perception is primarily a cognitive activity, involving the accurate appraisal of risk both externally and internally (Sitkin & Pablo, 1992).

Differences in risk perceptions lie at the source of many conflicts and communication failures between individuals (Weber & Hsee, 1998). Variations in risk perceptions are just as damaging to the financial planning process. Differences between parties in the perception of risk have a direct impact on individuals' risk decisions. Weber and Milliman (1997) showed a number of ways that individuals' overall risk decisions are a function of how the risk is actually perceived. Distinguishing between risk perception and other factors of risk is important because perception points to a unique locus in the decision-making process (Weber & Hsee, 1998; Klos, Weber, & Weber, 2005). That is, individuals' perception of risk corresponds to a distinct psychological trigger that influences the risk decision. The literature suggests that individuals' perception does influence the overall risk decision. This research explored how much perception influenced the risk decision, when combined with several other factors.

Risk perception is influenced by a number of factors, including previous risk decisions, aspiration levels, trust, expectations, and loss functions (Weber & Hsee, 1998). Other literature supports these components of risk perception (Odean, 1998; Nasic & Weber, 2010). Different factors lead to dissimilarities in risk perception as well. Framing, or how a risk proposition is presented, affects one's perception towards a risk decision (Vlaev, Chater, & Stewart, 2009). Although there is some context around the predictive nature of risk perception in the risk decision (Klos et al., 2005), future studies are needed to explore the strength of the relationship.

There are a number of behavioral biases, now commonly discussed in the literature, that influence an individual's perception of risk. These behaviors include, but are not limited to, overconfidence, effects of the past, representativeness, mood, and familiarity. Since it is difficult to know which behavioral biases affect an individual's perception of risk the most, it is important for researchers to be familiar with some of the most common perception-influencing factors. A

general discussion regarding some of the behaviors influencing risk perception will follow.

Individuals tend to be overconfident by nature (Nofsinger, 2010). People have a natural tendency to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. Other researchers concur (Bukzar, 2003; Heath & Suls, 2004; Weinstein, 1980). Further, overconfidence causes individuals to credit themselves for successes, and blame external factors for their failures (Kitces, 2006). Examples of overconfidence in typical financial situations include excessive trading and overly optimistic estimates of investment performance. Additionally, individuals illustrate overconfidence when they have the belief that they can control an outcome based on the amount of information they have, or the amount of times they perform a task. From a risk perception standpoint, this kind of behavior leads to the individual becoming excessively confident and overestimating the likelihood of future success, and consequently discredits data that may otherwise assist the financial advisor in accurately assessing risk (Kitces, 2006). Individuals also have the tendency to experience stronger negative feelings from losses than from gains (Kahneman & Tversky, 1979). As a result, people put more weight on the negative feelings resulting from their failures, and become excessively averse to them. Therefore, an individual's risk perception can be altered dramatically from a negative experience. In other words, a loss that an individual remembers, or has experienced, can influence perception much more than a potential loss that has not been experienced. Overconfidence affects individuals' forecasts as well. If someone has success in their ability to accurately predict past outcomes, the individual may become overconfident with future predictions (Hilary & Menzly, 2006; Langer, 1975). When this is the case, overconfident individuals will perceive their decisions as less risky than they really are (Nofsinger, 2010).

The past can have a tremendous impact on an individual's perception of risk. People are

willing to take more risk after earning gains and less risk after earning losses (Thaler & Johnson, 1990). Gamblers refer to this feeling as “playing with the house's money.” Conversely, the same can be said after individuals experience a financial loss. When faced with a risk decision after a negative outcome, individuals generally do not choose the risky decision (Ackert, Charupat, Church, & Deaves, 2005). Although these actions do not always occur, the past does play an increasingly important role in shaping the risk perception of individuals (Nofsinger, 2010). Classifying a decision frame based on past results ignores the present and future. Nonetheless, those who use the past to influence their decision-making process often miscalculate their choice (Solt & Statman, 1989).

The past performance of investments has an influence on individuals. Despite the prevalent warnings that past performance in no way predicts future results, individuals seem to act differently. When using past data, numerous studies have found that retail money flows into mutual funds or investments that have above-average track records (De Bondt, 1993; De Bondt & Thaler, 1985; Ippolito, 1992; Kane, Santini, & Aber, 1991; Patel, Hendricks, & Zeckhauser, 1990), providing evidence that investors will seek out a choice that appears to predict the future. This irrational mentality differs from traditional frameworks that state that individuals will act in an unbiased fashion. Sometimes, individuals adjust their decisions to justify occurrences of the past. In this phenomenon, known as cognitive dissonance (Festinger, 1957), decision makers have a discrepancy between actual evidence and past choices, so they alter their decisions to help reduce the pain experienced at an earlier time (Goetzmann & Peles, 1997). Essentially, individuals' current beliefs conform to their prior actions. For example, Erlich, Guttman, Schonback, and Mills (1957) found that consumers selectively noticed car advertisements that reinforced their recent car-buying decision. The ads made them feel better about the decision

they had just made. Cognitive dissonance affects an individual's risk perception in that it causes the individual to make a risk decision based on a prior outcome. Therefore, the effects of the past must be taken into consideration when gauging one's perception of risk.

Representativeness is another trait that can affect an individual's risk perception. With respect to investing, there is an old adage that investors often confuse a good company with a good investment. This is a simple example of how someone can confuse a decision that is risky and one that is not (Nofsinger, 2010). Further, representativeness causes some individuals to underestimate (or overestimate) one type of risk, and make it representative of a broader series of risks. For example, losing money in a mutual fund makes some individuals shy away from owning any mutual funds in the future (Kitces, 2006).

When someone is influenced by representativeness, he or she is under the impression that an event that has recently occurred is likely to continue, and therefore represents the likely outcome going forward. Another example of representativeness is the assumption that a company that has generated strong earnings will continue to do so solely based on past performance. This is not always the case, and therefore it can be troubling when past events are assumed to be an accurate representation of future outcomes (Baker & Nofsinger, 2002). Representativeness affects individuals' perception of risk because it creates a false sense of reality. Investments that have had a poor period may be considered losers by the decision maker. However, considering this past performance to be a realistic predictor of the future may lead to an inaccurate assessment (De Bondt & Thaler, 1985). Additionally, it can cause the individual to gauge the investment to be less (or more) risky than it really is. Therefore, the past, although it should not, affects an individual's current decisions.

Familiarity bias is an issue worth addressing in the risk-assessment process. Individuals

that exhibit this behavioral finance bias tend to choose things they are familiar with. In investing, familiarity bias is illustrated when investors buy a disproportionate amount of securities from their own country, despite the well-documented benefits associated with international diversification (Baker & Nofsinger, 2002). If an individual is not familiar with a particular area of financial planning or event, he or she may view it as more risky than something familiar. This may be a dangerously incorrect assumption to make in the risk-evaluation process. Generally, people prefer things that are familiar to them. When people are faced with two risky choices, and they know more about one than the other, they will pick the more familiar option. However, the selection is not necessarily the less risky alternative (Heath & Tversky, 1991). This type of behavior affects risk perception. Another example of this behavior is seen in those who hold excessive amounts of stock in the company at which they work. They have extreme comfort, or familiarity, with the company, which can lead the individual to have an incorrect perception of the risk associated with the company. Again, this person's perception of risk may be flawed. The individual may underestimate the amount of risk that is inherent in the company's stock.

The familiarity bias also contributes to individuals' tendency to favor domestic investments, relative to international securities, in their portfolios (French & Roberta, 1991; Graham, Harvey, & Huang, 2009; Lewis, 1999). When individuals feel less comfortable or familiar with foreign assets, they are less likely to invest in these types of securities. Conversely, investors are more apt to invest in their "home countries" because of the familiarity and understanding they have with their geographic area. From a risk perception point of view, the familiarity bias forces decision makers to underestimate the risks of their "home country," and overestimate the risks of foreign countries.

Investment planning is not the only part of the financial planning process where the

familiarity bias is present. The behavior has also been found in real estate planning and lending (Seiler, Seiler, Traub, & Harrison, 2008). Homeowners sometimes view their residences as less risky than other properties. When asked, individuals perceive their homes as having less downside risk than the homes in their geographic area. The research indicates that this is due to the familiarity bias; homeowners are more familiar with their property, so they view it as less risky than other, comparable pieces of real estate. Further, this familiarity bias becomes greater the further away the homeowners' comparable properties become. So, the less familiar individuals are with other homes, the more risky they view them. The familiarity bias in this part of the financial planning process has adverse effects as well. If homeowners believe their property is prone to risk, it may affect their financing decisions. For example, a borrower may delay refinancing a high-rate adjustable mortgage during a suppressed market, if the individual really believes the home's value will remain high. Ultimately, this decision (impacted by the familiarity bias) may force the borrower to produce more capital to refinance a significantly higher loan-to-value ratio. This kind of occurrence would have a "domino effect" on the rest of the personal financial plan. It may cause the individual to sell long-term investments, save less, or tap savings. Overall, the familiarity bias has far-reaching effects on individuals' risk perception, and it can alter the way decision makers view risk in many different ways.

Risk Composure

Risk composure is an instrumental factor in the risk decision-making process. Individuals' risk composure will be an increasingly valuable element in helping both financial advisors and their clients evaluate plans in a more dynamic manner. Risk composure refers to the notion that planners can infer something about their client's behavior toward risk by reviewing the client's real-life decisions in financial situations (Cordell, 2002). Since risk composure is the

evaluation of how an individual actually behaves in the presence of a risky situation, it should be a component of the risk decision-making process. Individuals' composure in the presence of risk could be seen during the 2008 financial crisis. For example, those who exhibited a low composure would have been more likely to sell stocks when they should not have, abandoning their financial plan and increasing the likelihood of plan failure. Individuals who have a high risk composure are more likely to stick with their long-term plans and be less affected by risk when they actually face it (Egan, 2012).

Research theorizes that an individual's risk composure refers to his/her current tendency to take or avoid risk (Pablo, 1997; Sitkin & Pablo, 1992; Sitkin & Weingart, 1995). This means that risk composure is a personality attribute that reflects the individual's actual tendency to take or avoid risk. Composure can change over time as the individual is exposed to various experiences. Risk composure is a useful indicator of how people make decisions under actual risk conditions (Hung & Tangpong, 2010). Therefore, neglecting to account for one's actual behavior in the presence of risk is problematic. Risk composure addresses an individual's behavior in an actual risk decision situation, as opposed to other risk constructs that look at hypothetical situations. Simulated gauges of risk are fundamental components of risk-assessment, but if individuals abandon a plan because of adverse circumstances, undesirable outcomes may occur. Knowing how an individual has responded to uncertainty in the past may better prepare advisors to assist their clients. If individuals' risk composure differs from other risk factors, there could be variances between how an individual says they will act and how they actually behave. For example, an individual with a high tolerance for risk may be willing to incur a significant amount of volatility, in a hypothetical portfolio or financial plan. However, if that same person has a low risk composure, unforeseen economic or financial conditions may drive

the decisions they make. During these situations, these individuals may sell assets, or engage in other behaviors that contradict their willingness to bear risk (Stokes, 2010). Egan (2012) cited similar findings. Whereas some individuals may feel willing to take risk in the long term, they may not feel the same in the short term.

Sitkin and Pablo (1992) proposed that risk composure is not only different than risk tolerance, but that it is also a vital construct in the risk-assessment process. For the purposes of this research, risk composure was defined as how an individual behaves, or acts, in the presence of risk. Said another way, composure is a measure of a person's actual behavior when faced with a financial risk decision (Cordell, 2001). The questions used in this study to assess composure focused on how an individual behaved in the past, when faced with a risky financial situation.

Risk Knowledge

Many risk-assessment processes lack the incorporation of a person's financial risk knowledge into the evaluation. If knowledge is not accounted for in the risk-assessment process, an inaccurate estimate of risk may occur (Cordell, 2001). This behavior may not only lead to inconsistent assessment results, but it may also be an indicator that the individual has low financial knowledge. Risk knowledge refers to an individual's understanding of risk and risk/return trade-offs. It is widely accepted that those who understand the nature of risk (and thus have higher risk knowledge) are more likely to accept or seek asset allocation models or financial plans that are consistent with the accomplishment of their goals (Cordell, 2001).

It is important to note that the risk construct explored in this study is different from the general financial knowledge construct used heavily in the literature. To accurately assess risk knowledge, it is important to determine the individual's understanding of the risk/return relationship specifically. For example, individuals may have a high financial knowledge, but a

low understanding of the risk/return relationship. This knowledge may also feed into other risk-profiling constructs (such as composure) in helping individuals resist the temptation of panicking when circumstances like bear markets occur. Theoretically, knowledge of how financial markets operate should result in individuals making more effective financial decisions (Liebermann & Flint-Goor, 1996). Numerous other studies have found that well-developed financial skills are necessary for effective financial management, and that individuals' financial knowledge significantly affects their financial behavior (Haynes-Bordas, Kiss & Yilmazer, 2008; Hilgert, Hogarth, & Beverly, 2003; Perry & Morris, 2005; Robb & Woodyard, 2011). Other studies have concluded that individuals' lack of knowledge could lead to unfavorable financial environments unless efforts to increase financial knowledge are improved upon (Taylor & Overbey, 1999; O'Neil, Bristow, & Brennan, 1999). Other research suggests a more specific relationship between knowledge and risk. There is an abundance of literature recognizing the positive correlation between individuals' risk levels and financial knowledge (Ahmad, Safwan, Ali, & Tabasum, 2011; Carducci & Wong, 1998; Grable, 2000; Haliassos & Bertaut, 1995; Sung & Hanna, 1996). Based on these findings, it is imperative that financial risk knowledge be incorporated into the risk-profiling process.

There is uncertainty with respect to how risk knowledge should be measured. There are three distinct ways in which financial knowledge can be calculated: (a) objectively, (b) subjectively, and (c) experientially (Flynn & Goldsmith, 1999). Cordell (2001) suggested that there is no adequate way to measure risk knowledge other than with a financial advisor's subjective gauging. However, subjective judgments of risk knowledge may not be the most accurate measure of the construct, especially when there are objective measures available. When objective and subjective financial knowledge have been measured comparatively, more than half

of individuals who believed they had a fair amount of financial knowledge actually did not (Courchane, 2005). This effect is due to individuals' tendency to be overconfident.

Overconfident individuals distort their perception of their skills and experience in financial matters, which does not result in an accurate representation of reality (Charupat, Deaves, & Luders, 2005). This behavior can be dangerous in the financial planning process. Specifically, it can lead to mistakes such as under-diversification and/or excessive trading. For the purposes of this study, questions on the subject of risk knowledge were borrowed from previous studies, and were objective in nature.

Risk Preference

According to Modern Portfolio Theory (MPT), when given a choice in a risk decision, individuals will prefer the option that maximizes returns with the least amount of risk (Markowitz, 1952). Seminal frameworks like MPT and the Capital Asset Pricing Model (Sharpe, 1964) assume that individuals are rational, and that they are inherently risk-averse. Newer frameworks add to this claim by adding qualifying factors to the risk decision. Prospect theory suggests that different decision frames can lead to different choices (Kahneman & Tversky, 1979). This effect occurs because individuals tend to be more risk-averse when their choices are described in a positive domain, and more risk-seeking when the alternatives are described in a negative domain (Wang & Fishbeck, 2004). Therefore, prospect theory describes individuals' tendency to prefer risk alternatives in choices that involve sure losses, and to seek risk-aversion in circumstances that involve sure gains. These findings cannot be explained by EU theory, which states that individuals' decisions should not be impacted by how choices are presented. According to prospect theory, there are two distinct levels of the decision-making process. The first is an editing stage where an individual weighs the alternatives of the decision. In this phase,

the decision maker evaluates the prospects based on a reference, or anchor, point. The next part of the decision, termed the evaluation stage, involves a modeling approach that uses value functions to estimate preferences for each choice. These value functions are similar to traditional economic utility functions, but they weight the subjective value of each outcome by a decision value. These value functions are weighted more heavily for losses than they are for gains, accounting for individuals' preference to avoid loss.

Other studies have expanded on this framework by finding that individuals *prefer* risk when their investment returns are below a certain reference point. The same individuals do not prefer risk when their investment returns are above the reference point (Chou, Chou, & Ko, 2009). Further research has coined this type of behavior as the disposition effect (Odean, 1998). Niendorf and Ottaway (2002) also found that individuals' preferences for risk change. When individuals vary the way they participate in a behavior in different situations, their preferences for risk may change. That is, individuals demonstrate different risk preferences depending on the financial conditions. This type of behavior is not consistent with traditional logic that states that individuals' preference for risk will stay the same, across time, and through varying financial conditions. Risk preferences can, and actually do, vary across both time and financial conditions. Weber and Hsee (1998) found that individuals demonstrate varying risk preferences. Their research found that respondents had varying risk preferences in options purchases. These findings are significant to the risk-assessment process. It counters the traditional thought that individuals prefer to be risk-averse. Therefore, it is vital that an individual's unique preference for risk is understood in the evaluation process.

The way in which a decision choice is asked, or framed, to individuals often influences the choice (Nofsinger, 2010). Decision makers should select the same choice, regardless of

whether or not the choice is proposed in a positive or negative manner. However, Tversky and Kahneman (1981) found that this is not the case. They noted that people make decisions based on the frame of the choice presented. These outcomes are an extension of prospect theory. The framework explains individuals' tendency to select the less risky choice when it is presented to them in a positive frame, and to choose the risky option when the choice is framed in a negative domain. The effects of prospect theory and these framing effects are far-reaching in the evaluation of individuals' risk preference. First, risk preference questions must be asked in such a way that framing effects are minimized. Specifically, the way in which questions are asked should not affect the answer given, or the decision that is made. However, this is not always the case (Madrian & Shea, 2001; Nofsinger, 2005; Tversky & Kahneman, 1974; Tversky & Kahneman, 1981). The effects of framing may have an effect on the risk decision, creating an inaccurate assessment result. Tversky and Kahneman (1981) were among the first to find that individuals make different choices depending on the framing of a particular question. Questions attempting to assess risk preference should not overemphasize positive or negative outcomes, but rather remain neutral in context. Next, prospect theory explains that individuals do not always make decisions based on the framework of traditional expected utility functions. Therefore, by assessing risk preference, these psychological components could be factored into the decision-making process. Given that taking a financial risk is most often a choice, participants in this study were given the option of selecting a scenario that they would favor, or prefer. Because individuals' behavior, as well as their wealth changes, affect their preference to take risk, assessments that take preference into consideration must be used to accurately estimate a risk profile. Risk preference, as applied in this study, referred to a person's psychological preference to take a certain level of risk in return for a potential reward (Kitces, 2006).

Risk Need

An individual's risk need, which is defined as the level of return required (i.e., needed) to reach a financial goal (Grable & Lytton, 1999), is another objective factor that influences risk-evaluation. Knowing the amount of risk needed to fulfill an individual's goals is equally as instrumental. It is also important that advisors' and clients' definitions of variables like risk and return are the same throughout the risk-assessment process. Often times they are not, and this can cause confusion when trying to obtain an accurate risk-evaluation measure (Snelbecker, Roszkowski, & Cutler, 1990). Variables significant to the risk-assessment process such as risk and return should be adequately defined, so that misinterpretations cannot occur. This will increase the probability of inaccurate risk estimates, and further negatively affect the financial plan.

Delequie (2008) discovered that it is beneficial to focus on the concept of maximum acceptable loss during the risk-assessment process. If both the client and the advisor have a clear understanding of the client's absolute and relative maximum acceptable loss, risk can be more accurately assessed. Although devoting an entire survey to one's maximum acceptable loss may be unnecessary, focusing some part of the questionnaire on the subject is worthwhile. If respondents know the worst-case scenario that they can tolerate within their financial plan, they may have a better understanding of their overall financial risk-estimation.

Because individuals may have more than one goal, it is important to evaluate the risk need for each one of these goals, especially the top two or three goals that the individuals would perceive as their primary needs. Additionally, individuals may be required to take different levels of risk to accomplish each goal that they have. Therefore, it is important that each goal's risk need be assessed. For example, suppose saving for a child's college is a family's primary goal. If the family already has a significant amount of money saved for their child's education expenses,

and much of the planning has already been completed with respect to the education plan, there is a very low need to take risk with respect to how the funds earmarked for education should grow. This goal, subsequently, would be characterized as having a low risk need. Conversely, assume those same individuals were also saving for retirement, had a moderate time horizon to do so, and had very little savings already. These individuals would have a high risk need, relative to the goal of saving for retirement. As such, in this study, risk need was defined as an individual's need to take financial risk in order to fulfill his/her financial goals.

Summary

Some financial institutions are already attempting to utilize a multidimensional form of risk-assessment. For example, at U.K.-based Barclay's, the concepts of behavioral finance are intertwined in the assessment clients' risk levels, and ultimately, the management of their assets. Their comprehensive method of assessment includes three risk components: risk tolerance, risk composure, and market risk engagement. The goal, in addition to an accurate method of risk-assessment, is to provide financial advisors with a tool for a more accurate assessment of their client's mindset when it comes to money. Barclay's risk-assessment tool recognizes that although individuals may have a high willingness (tolerance) to accept risk over the long term, they may be very impulsive when actually presented with risk (low risk composure). Utilizing a multifaceted approach to the risk-assessment process better enables financial advisors to understand how to work with clients who have differences among the risk constructs (Lee, 2011).

When it comes to risk questionnaires, one thing is clear: the tools can vary tremendously (Grable & Joo, 2000). Due to the increasingly complex and comprehensive financial planning environment, a method of analysis to assess risk should be equally as encompassing. The

problem is that, currently, one does not exist. A risk-assessment process that is both user-friendly and efficient as well as comprehensive should be utilized. Additionally, assessments that are solely objective in nature may be influenced by the selection bias, or other prejudices (Yao et al., 2004). Further, objective measures of assessment assume that individuals act in a rational manner, and that their asset allocation is a result of personal choice rather than the advice of a third party. As a result, objective measures (a) tend to be descriptive rather than predictive, (b) do not account for the multidimensional nature of risk, and (c) often fail to explain actual individual behavior (Elvekrog, 1996; Train, 1995). Instead of relying more on standardized measures of risk, or empirically tested rules, many individuals and advisors rely on one-dimensional assessments and objective measures to gauge individuals' risk propensities. Despite this, objective measures are instrumental in understanding certain aspects of individuals' risk-assessment (e.g., risk capacity). Purely subjective measures of risk-assessment lack standardized measures, and tend to lack a theoretical framework (Grable & Lytton, 2001; Cai & Yang, 2010). However, individuals do a fairly good job in assessing their own subjective risk measures, when given the right factors (Grable, Roszkowski, Joo, O'Neill, & Lytton, 2009). A method that utilizes both subjective and objective measures will best serve the financial services industry and individuals going forward.

To date, no assessments take all of these risk-assessment variables into consideration. Often assessment tools focus on only one risk component, or a couple of risk constructs. While it is still uncertain which of these variables should be utilized when assessing risk, little research has been conducted to test the effects of the constructs collectively on the risk decision. Hanna and Chen (1997) defined risk-assessment as accurately analyzing one's capacity for risk. However, taking only an individual's ability to withstand loss into consideration may make for

an unsustainable financial planning environment for the individual, if there are other factors that the individual deems risky. These factors would include the other risk constructs utilized in this study such as risk tolerance, risk capacity, risk perception, risk composure, risk knowledge, risk preference, and risk need. Single-dimension methods of risk-assessment often fail in predicting someone's risk accurately and completely. Part of what this research did was to test whether or not a more complete assessment of risk is more effective than single-dimension measures in analyzing individuals' risk propensities.

Furthermore, any risk surveys used to date do not take into consideration emotional or irrational behavior that many individuals exhibit in the financial planning process. One of the results of current assessment techniques in portfolio management is that lower portfolio turnover and less frequent changes lead to better performance (Barber & Odean, 2001; Glaser & Weber, 2007; Odean, 1999; Statman, Thorley, & Vorkink, 2006). However, recent behavioral finance research shows that individuals actually prefer frequent changes to their portfolios (Charness & Gneezy, 2010). This choice to engage in risky investment behavior goes against the widely accepted rationale that individuals will choose the portfolio with lower turnover because of lower expenses, taxes, and underperformance. Often, individuals act on emotion, rather than theory and logic. Nasic and Weber (2010) found that behaviors like attitude and emotion determine how an individual invests.

Although the literature has explored differences between some of the risk-assessment variables that were incorporated into this study, there is little research exploring the associations between and among them in what this dissertation terms a Comprehensive Risk Profile (CRP) model. Additionally, other than Cordell's (2001) four-dimension risk-assessment tool and Hanna et al.'s (2008) conceptual model, little research has been conducted to test the effectiveness of

more comprehensive financial risk-assessment measures.

This study expanded upon Hanna et al.'s (2008) framework by exploring the association among several risk-profiling variables. These constructs included risk tolerance, risk perception, risk preference, risk composure, risk need, risk knowledge, and risk capacity. Additionally, the research discussed the impact that individual risk-assessment variables have on one's overall risk, and which variables affect one's overall risk-assessment the most. Lastly, this analysis utilized these risk-assessment variables to develop a comprehensive measure of financial risk.

Significance of the Study

This research provided a substantial contribution to the financial risk-assessment literature. First, it explored the associations between various risk constructs. Additionally, this study determined if there are any associations between the different risk constructs that many academics and practitioners use, sometimes as a proxy for risk-assessment. Further, analysis showed that the risk construct is not the only variable academics and practitioners should account for in the assessment process. Perhaps one of the most instrumental parts of this research is that it produced a comprehensive tool for risk-assessment. This profile can be used as an individual's inclusive risk measure, formed by combining a collection of risk-assessment variables. The assessment is unique in that it combines several risk constructs, as opposed to current methods, which utilize a much smaller spectrum of risk-assessment variables, into an optimally weighted CRP scale. Therefore, the research uncovered which risk-assessment variables matter the most when assessing an individual's overall risk, and which constructs have the most significant impact on individuals' overall asset allocation targets. Lastly, the results from this study could help move the financial services profession closer to an accurate, uniform, all-encompassing method of risk-assessment that is easy and efficient to implement.

Financial advisors are in the difficult position of providing advice that is rooted in rational theory, but also manage and understand the behaviors of their clients (Finke et al., 2008). An accurate method of risk-assessment, and a thorough understanding of the factors that predict individuals' financial behavior, will make this process more manageable. This may mean that the term "risk tolerance" is no longer used interchangeably with assessing an individual's CRP. This study produced a comprehensive and accurate method of assessment, by identifying risk constructs that are the most impactful to an individual's CRP, and explaining the associations among financial risk-assessment variables.

The results of this study were exploratory, yet helpful, both in the field of financial planning, as well as in academia. Although there are a number of methods available, practitioners have no uniform method of financial risk-assessment, nor do they have a tool that encompasses the comprehensive set of constructs that this research provides. Additionally, advisors will be able to see the varying aspects of risk that their clients have. For example, a client may have a very low risk composure, but a very high risk tolerance. Planners will be able to work with their clients to discuss these areas of risk-evaluation, and educate their clients on what each means. The assessment tool should be well received among financial institutions, as it will provide a more comprehensive measure of assessment than most profiles currently being used, and it is also efficient. The comprehensive nature of the tool is, and will continue to be, very important in the field of financial planning as the trend towards increased regulation and financial institution oversight continues. It also provides these institutions with a more accurate risk profile, reducing the liability of the financial institutions and their advisors. Academia can apply this study towards future research as well. Since it is exploratory in nature, future work will need to be done to test the concepts in other geographic areas, with a more diverse

demographic, to improve the validity. Further, it would be ideal to develop a model to assess individuals' overall financial risk (as the outcome variable), not just their asset allocation. Researchers can use this study as a springboard for these kinds of future tests. Additionally, academics can apply this research, and this risk profile, to future financial risk studies. In addition to the traditional methods of assessment such as the SCF question or the Grable and Lytton (1999) tool, this assessment can be applied to future studies to cover a wider range of financial risk constructs.

Chapter 3 - Methodology

The purpose of this study was to apply one particular aspect of Coleman's (2007) conceptual model of financial risk-taking by expanding on the work of Hanna and his associates (2008). As discussed in Chapter 1, the study tested the following:

1. *The associations among independent risk-assessment variables.*
2. *The concept that prudent financial risk-assessment goes beyond estimating an individual's risk tolerance.*
3. *The impact that each risk variable has on an individual's overall Comprehensive Risk Profile (CRP).*
4. *A comprehensive method of risk-assessment to estimate an individual's overall risk profile.*
5. *The development of a weighted risk profile score and its assignment to a target asset allocation model.*

The methodology applied was intended to help uncover which risk-assessment variables impact an individual's overall risk profile the most, and to determine which risk components should be more heavily weighted in the risk-evaluation process. Further, the data showed how much these risk factors should contribute to an overall model of risk-assessment. This work added to the existing literature by challenging the belief that risk tolerance is the only, or primary, factor of interest in the prudent assessment of one's financial risk. Ultimately, it is hoped that this dissertation will help move the financial planning field closer to an accurate, uniform, all-encompassing method of risk-assessment that is easy to implement.

Empirical Model

It is generally accepted as true that individuals' risk-assessments ought to be a predictor of the actual risk that they incur with their financial plan (Davey, 2012). For the purposes of this study, responses to a series of risk-assessment items, each of which is designed to measure a distinct aspect of a person's risk profile, were used to develop a comprehensive measure that can be used by financial advisors and consumers as a tool within the planning process. A specific outcome associated with this project involved matching risk profile scores to targeted asset allocations, as defined by a Delphi group of experts. As discussed in Chapter 1, this study expanded on an operationalized framework presented by Hanna et al. (2008). Their framework is hypothesized, in this study, to be a proxy for what Coleman (2007) called a Decision Maker's Risk Profile. As noted in the literature review, this dissertation added to the existing literature, primarily by expanding the possible factors that make up someone's risk profile. Figure 3.1 illustrates how the Hanna et al. (2008) conceptualization is operationalized in this study. The remainder of this chapter is devoted to describing how each construct in Figure 3.1 was assessed, and how the model was tested.

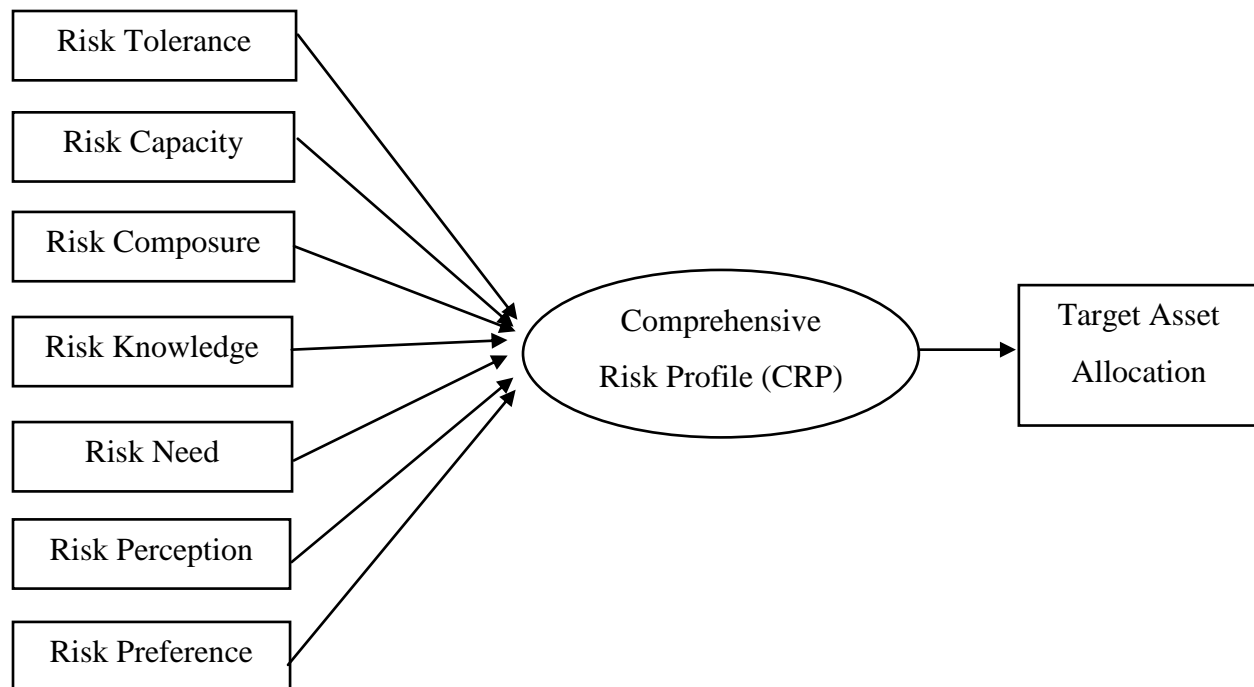


Figure 3.1 The Empirical (Operationalized) Model for the Comprehensive Risk Profile

Research Propositions

Several important associations are apparent in Figure 3.1. In effect, a person’s Comprehensive Risk Profile (CRP) is hypothesized to be comprised of seven factors. CRP, as defined in this study, is a latent variable. That is, CRP scores are not observable directly, but rather derived from seven measured inputs. It is important to note that it is yet unknown whether an individual’s CRP is composed of seven distinct risk factors or a combination of factors. A significant outcome associated with this study involved answering this key question.

Additionally, some of the factors themselves may have several components. As illustrated in Figure 3.1, CRP is hypothesized to be dependent on seven distinct factors. It is possible, however, that there may be fewer than seven factors that account for a CRP score. Determining the precise, weighted number of factors associated with CRP scores was a primary outcome of

this study.

A number of propositions were explored as a component of this research. Specifically, this study proposed the following:

Proposition One. Risk tolerance, risk perception, risk preference, risk capacity, risk composure, risk knowledge, and risk need will be statistically associated with one another.

Proposition Two. Risk tolerance, risk perception, risk preference, risk capacity, risk composure, risk knowledge, and risk need contribute meaningfully to an individual's Comprehensive Risk Profile (CRP).

Proposition Three. Risk tolerance, risk perception, risk preference, risk capacity, risk composure, risk knowledge, and risk need can be combined into a weighted risk profiling score.

Proposition Four. Comprehensive risk profiling scores can be matched to a target asset allocation model.

Sample

The primary data for this study was obtained using a combination of three different convenience samples. The participants from the first sample set were clients of a financial advisory practice, most of whom lived in the South. These clients were offered the opportunity to participate in the study as a part of routine financial review meetings with their financial advisors. There were approximately 100 participants in this part of the data collection. Additional data was collected from respondents at a neighborhood barbershop. Four \$25 gift cards were awarded to randomly selected participants from the sampling. The third data set was collected from two different high school faculties, one from a school in the South, another from a

school in the Mid-Atlantic. Respondents from this sample were asked to voluntarily fill out the surveys during a teacher workday. Based on the geographic demographic, the sample was predominantly retirees, with an adequate mix of gender. One of the main purposes of this study was to establish a testable risk-assessment instrument. Therefore, a convenience sampling was adequate. Future studies should be conducted to test the instrument (and other findings of this research) with different samples. In total, between both sampling methods, there were 321 respondents from the primary data collection. Given a power analysis, this sample size is estimated to be appropriate for an exploratory study.

Measures

The appropriate length of the questionnaire is an important factor to determine as well. Grable and Lytton (1999a,b) identified many different options for newer, modified risk questionnaires. They explored not just the types of questions asked, but also the length of the survey itself. The number of questions can range from 1 to over 100, so there is a wide range of variability. Although fewer survey questions may increase the likelihood of a respondent's attention, it does not make the survey more valid. In fact, most researchers agree that the deeper a risk-evaluation questionnaire is, the better chance one has at an accurate risk-assessment. Many traditional surveys are far too short to be valid measures of estimating risk (Roszkowski et al., 2005). However, there should be a balance between thoroughness and efficiency. Surveys that are too long in length may cause respondents to rush their answers, to reply to the questions less than to the best of their ability, or to avoid using the questionnaire entirely. This would decrease the accuracy of the assessment, or the chance that it is even used. Heberlein and Baumgartner (1978) noted additional risk-assessment rules. Their research found that risk surveys with more items actually get lower response rates. Roszkowski and Bean (1990) had similar findings. That

is, they found that risk questionnaire length is inversely related to individuals' response rate. Therefore, there is an appropriate length for the questionnaire. If the survey is too long, lower response rates will occur. However, if the questionnaire is too short, it may not do an accurate job in fully assessing an individual's CRP.

Surveys vary in length, question structure, terminology, depth of content, and method of analysis. Although it remains uncertain which questionnaire is the most accurate estimator of a risk profile, many researchers agree that a diversified approach is important until a standard method is accepted (Roszkowski, 1992). Although there remain multiple variations of the questionnaire, combining methods may be the best approach since a multidimensional approach includes questions and areas of all aspects of risk-assessment. A multifaceted approach includes traditional risk-assessment questions, but also incorporates behavioral and emotional aspects (MacCrimmon, Wehrung, & Stanbury, 1986). Because it remains unclear which questionnaire is the most accurate in assessing an individual's risk profile, combining multiple assessment techniques may be prudent. Further, it is unclear whether or not variations in the risk questionnaire alter the assessment process.

The Comprehensive Risk Profile Tool

The participants in this study completed a 14-item, multiple choice risk-assessment questionnaire called the Comprehensive Risk Profile (CRP) questionnaire. This paper survey included two questions for each of the seven risk constructs. Each of the responses were scored using the following scale for each of the four choices to a question: a = 1, b = 2, c = 3, and d = 4. The exception to this scoring was with the risk knowledge items. For question 11 (the first risk knowledge question), "a," "c," and "d" responses were all coded with a "1," reflecting an incorrect response. Correct responses ("b") were coded with a "4." Since question 12 (the

second risk knowledge item) was a true/false option, correct responses (“b”) were scored with a “4,” and incorrect answers (“a”) were coded with a “1.” A factor analysis was then conducted to see which risk profile variables could be grouped together. Then, the factors were weighted, depending on the factor’s contribution to the model’s explained variance. The weighted scores of each factor were summated to develop an individual’s CRP score. The risk knowledge responses were given a slightly altered score, since there were only two responses. Correct answers were scored as a “4,” while wrong answers were coded as a “1.” Additionally, the first risk capacity item was coded differently. Since responses to each choice were denoted with a yes/no response, each “yes” response was given a value of “1,” whereas each “no” response was given a value of “0.” The total value for the variable was a result of the summated value of the responses. For example, if the respondent answers the question with three “yes” responses, his/her risk capacity score would be given a “3.” Outcome scores for the CRP were then distributed into five target asset allocation models, based on the respondent’s CRP score.

Independent Variables

There were seven constructs in this study that were used to assess individuals’ CRP, as well as help in the development of each respondent’s optimal asset allocation. All of the variables utilized in the research have been discussed in previous literature, or prior risk surveys. However, they have never been used collectively to assess a risk profile this comprehensively. Both the definitions of the constructs, as well as the questions used in the survey, were borrowed from prior work to increase the reliability and validity of the study and its results.

Risk Tolerance

Although the term risk tolerance may be used interchangeably to describe one’s holistic maximum level of acceptable risk, the term was utilized much more specifically in this

study. This research adopted Cordell's (2001) definition as follows: financial risk tolerance is the maximum amount of uncertainty that an individual is willing to accept when making a financial decision. To analyze this aspect of risk-evaluation, the Survey of Consumer Finances (SCF) risk tolerance question was applied to the study. The SCF risk tolerance question is the following:

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

- a. Not willing to take any financial risks (1 point)*
- b. Take average financial risks expecting to earn average returns (2 points)*
- c. Take above average financial risks expecting to earn above average returns (3 points)*
- d. Take substantial financial risk expecting to earn substantial returns (4 points)*

A second risk tolerance question was used to measure a person's willingness to engage in a risky financial behavior. The item, adapted from a Merrill Lynch client risk questionnaire read as follows:

How large of a decline in your investment's value would you be willing to accept in any one-year period? Assume for this example that your initial investment is worth \$100,000.

- a. Less than \$5,000*
- b. \$10,000*
- c. \$20,000*
- d. \$25,000 or more*

One anticipated outcome from this research was to determine both the reliability and validity of this item in the context of risk-estimation.

Risk Perception

Risk perception is distinctly different from other aspects of risk-evaluation (Roszkowski & Davey, 2010). Perception, while often used interchangeably with tolerance, is actually a distinct concept that contributes to risk-taking behavior (Sitkin & Pablo, 1992). Risk perception is primarily a cognitive activity, involving the accurate appraisal of risk both externally and internally. Using this definitional construct, the first risk perception question that was used in this study was borrowed from the scale that Grable and Lytton (1999) developed. It read:

When you think of the word “risk,” which of the following words comes to mind first?

- a. Loss*
- b. Uncertainty*
- c. Opportunity*
- d. Thrill*

The second risk perception question used in this research was adapted from a risk survey at Merrill Lynch. The question used in this study read as follows:

Assume that your financial plan is statistically likely to fail. Which of the following actions would you perceive as the most appropriate way to increase the likelihood of your financial plan’s success?

- a. Lowering your future expectations*
- b. Saving more*
- c. Selling assets*
- d. Taking on more risk with your investments*

Risk Preference

When given a choice between risk decisions, individuals will prefer the one that maximizes returns with the least amount of risk (Markowitz, 1952). Risk preference, as applied

in this study, referred to a person's psychological propensity to take a certain level of risk in return for a potential reward (Kitces, 2006). Given that taking a financial risk is most often a choice, participants in this study were given the option of selecting a scenario that they would favor. The questions used to assess risk preference were adapted and slightly altered from the Grable and Lytton (1999) risk tolerance scale. The first question read as follows:

Assume you had a portfolio with a balance of \$100,000. Given the best and worst case returns of the four investment choices below, which would you prefer over the course of a one-year period?

- a. \$10,000 gain best case; \$0 loss worst case; \$4,500 gain average case*
- b. \$18,000 gain best case; \$12,000 loss worst case; \$6,000 gain average case*
- c. \$26,000 gain best case; \$18,000 loss worst case; \$8,000 gain average case*
- d. \$35,000 gain best case; \$30,000 loss worst case; \$12,000 gain average case*

The second question read:

Suppose a relative left you an inheritance of \$100,000, stipulating in the will that you had to invest all of the money into one of the following choices. Which one would you prefer?

- a. A savings account or money market mutual fund*
- b. A mutual fund that owns stocks and bonds*
- c. A portfolio of 15 common stocks*
- d. Commodities like gold, silver, and oil*

Risk Capacity

Risk capacity is an evaluation component that can be measured objectively, as opposed to the subjective measures utilized previously. For the purpose of this study, risk capacity was defined as one's financial ability to withstand loss or a risk (Kitces, 2006; Cordell, 2001).

Individuals' financial ability was assessed using adequacy measures related to insurance, net worth, time horizon, and savings. The first risk capacity item was measured and evaluated using benchmarks advocated by Grable (2008). Specifically, risk capacity was gauged as follows:

Please answer the following by responding with a yes or no answer.

- a. Do you have a positive net worth (more assets than liabilities)?*
- b. Do you have an emergency fund equal to 4.5 months of living expenses (Could you live for 4.5 months simply on your savings)?*
- c. Do you have a savings ratio equal to 10% of your gross income (Do you save 10% of your gross income)?*
- d. Do you have an adequate amount of insurance (Do you have life insurance in place today?)?*

A person's decision time horizon is another important factor that affects an individual's evaluation of and capacity to engage in a risky financial behavior (Kitces, 2006; Cordell, 2001).

The following question was borrowed and slightly altered from Kitces (2006) and a Merrill Lynch (2013a) risk survey to include one's time horizon as a main component of risk capacity:

Which of the following describes the length of time until you retire (or make significant withdrawals from your portfolio)?

- a. 0-5 years*
- b. 6-10 years*
- c. 11-20 years*
- d. 21+ years*

Risk Composure

Risk composure, or a person's propensity to behave in a systematic way when faced with

a risk choice, is a concept that has received little attention in the literature. However, as the subject of behavioral finance becomes more prevalent as a tool in the financial planning process, individuals' risk composure will likely grow to be a valuable element in helping both financial advisors and their clients evaluate plans in a more dynamic manner. For the purposes of this research, risk composure was defined as how an individual behaves, or acts, in the presence of risk. Said another way, composure is a measure of a person's real-life behavior when faced with a financial decision (Cordell, 2001). The first question that was used in this study to assess composure focused on how an individual behaved in the past, when faced with a risky financial situation. This risk composure question, borrowed and altered from a Barclay's risk survey (2011), was as follows:

When a quality asset you own lost value, how did you react? Examples of assets include: real estate, stocks, bonds, gold, etc.

- a. I sold the asset*
- b. I sold some of the asset, but not all of it*
- c. I made no changes*
- d. I bought more of the asset*

Socialization factors, both environmental and personal, are known to impact the way in which a person evaluates risk. Media, friends, and social groups can affect both financial and risk decisions (Nofsinger, 2010). Therefore, a second risk propensity question was incorporated to measure these effects. It was borrowed and slightly altered from a study conducted by Hong, Kubik, and Stein (2004). The question read as follows:

How do outside influences such as friends, social groups, publications, or the media influence your financial decisions, such as investing in the stock market?

- a. *They have a very significant impact on my financial decisions*
- b. *They have an average impact on my financial decisions*
- c. *They have a little impact on my financial decisions*
- d. *They have very little to no impact on my financial decisions*

Risk Knowledge

Risk knowledge refers to an individual's understanding of risk and the risk/return trade-off. It is widely accepted that those who understand the nature of risk (and thus have a higher risk knowledge) are more likely to accept or seek asset allocation models or financial plans that are consistent with the accomplishment of their goals (Cordell, 2001). This knowledge may also feed into other risk constructs (such as composure) in helping individuals resist the temptation of panicking when circumstances like bear markets occur. For the purposes of this study, the questions on the subject of risk knowledge were borrowed from the FINRA Financial Capability Survey, and were objective in nature. The first question read:

If interest rates rise, what will typically happen to bond prices?

- a. *They will increase*
- b. *They will decrease*
- c. *They will stay the same*
- d. *There is no relationship between interest rates and bond prices*

The second question read:

True or False: Buying a single company's stock usually provides a safer return than a stock mutual fund.

- a. *True*
- b. *False*

Risk Need

The risk/return need, which is defined as the level of return required (i.e., needed) to reach a financial goal (Grable & Lytton, 1999), is another objective factor that influences risk-evaluation. The questions below, borrowed from Grable and Lytton's survey, were used to measure the amount of risk individuals need to take in order to accomplish their financial goal:

Given your current financial situation, which of the following describes your need to take risk with your finances, in order to accomplish your primary goal?

- a. I need to take extremely little to no financial risk to accomplish my goal*
- b. I need to take a little financial risk to accomplish my goal*
- c. I need to take a moderate amount of financial risk to accomplish my goal*
- d. I need to take considerable financial risk in order to accomplish my goal*

The same question can be asked to help determine how much risk respondents need to take to meet their secondary financial goals. That is, do individuals need to take more or less risk to accomplish their secondary financial goals? Asking the same question, but directing it towards another goal, allows individuals to determine their risk need for different goals. For example, does the respondent feel that he needs to take on more risk with his college savings account for his child (secondary goal) than his retirement savings (primary goal)?

Given your current financial situation, which of the following describes your need to take risk with your finances, in order to accomplish your secondary goal/ goals?

- a. I need to take extremely little to no financial risk to accomplish my goals*
- b. I need to take a little financial risk to accomplish my goals*
- c. I need to take a moderate amount of financial risk to accomplish my goals*
- d. I need to take considerable financial risk in order to accomplish my goals*

Validity Item

The issue of validity plays an important role in the development of financial risk-profiling assessment instruments (MacCrimmon & Wehrung, 1986; Roszkowski et al., 1993; Roszkowski, 1995, Roszkowski et al., 2005). The following discussion provides a brief outline of the validity concept as it relates to the development of a financial risk-profiling assessment instrument.

Validity issues play a critical role in the creation and use of instruments designed specifically to predict and measure behavioral attitudes (Babbie, 1983; Field, 2009; Grable & Lytton, 1999).

Face validity must be assured by combining, modifying, and integrating successfully used financial risk tolerance items. These types of items generally emerge from a review of previous research, but they may also be developed from empirical observation. Internal validation assures researchers that a relationship between individual items and the measure itself exist. Face validity was assessed upon the completion of the data analysis portion of this research (to be explained in further detail later in this document).

Additionally, the results from this research were tested to see if the content of the assessments corresponded to the content of the constructs they were designed to cover. Content validity requires the use of previously used, recognized subject matter to evaluate whether the tested items assess the defined content further than simply face validity (Field, 2009). The final step in the development of the 14-item risk-profiling assessment instrument involved a test of validity. This test was conducted by analyzing the instrument's content validity, which is defined as the extent to which one can be sure the Comprehensive Risk Profile (CRP) represents an individual's risk profile (Henerson et al., 1987; Litwin, 1995; Silva, 1993). Content validity is calculated as a correlation coefficient (Litwin, 1995).

In addition to the 14 items in the risk-assessment questionnaire, respondents were also asked to answer a risk-assessment item utilized by the Rutgers University investment risk

tolerance quiz (njaes.rutgers.edu/money/riskquiz, 2013). Content validity was tested using the single-item measure. The question read:

In general, how would your best friend describe you as a risk taker?

- a. A real gambler*
- b. Willing to take risks after completing adequate research*
- c. Cautious*
- d. A real risk avoider*

The responses to this item were used to validate the CRP score developed as a result of the study. Responses to this validity question are known to be associated with an individual's investment allocation towards risky investments. Theoretically, a higher risk score on an individual's CRP should be associated with a higher score on the validity item.

Significant consideration was given to how validity would be tested, and which item would be selected. The item selected offered a) a high degree of face validity, b) a comprehensive risk-profiling measure, c) relevance to the respondents, and d) ease of administration (Grable & Lytton, 1999; MacCrimmon & Wehrung, 1986). Although the Rutgers University item selected is a single-measure assessment, it is meant to be comprehensive in nature. There are few single-item measures of this kind. That is, although other single-item measures could have been used as a validity measure, many focus on one risk construct (e.g., the SCF question is a risk tolerance question), rather than providing a general, overall estimate. It is also important to note that the validity item was not meant to supersede, or be a more accurate measure of, the individual's risk profile. It was simply a measure that provided an indication that the results from the research are similar to other measures that have been previously used in research. One of the clear purposes of this study was to illustrate that a comprehensive,

appropriately weighted method of financial risk-assessment is more accurate than any single-item measure. However, using a previously tested, one-dimensional method like the Rutgers University question assisted in the content validity process for the comprehensive tool used in this study. The use of a simple, single-item measure to test validity was not only practical for the researcher, but also for the study's participants. Adding additional questions to the validity process, or using a question that was more difficult to interpret, may have not only caused the respondent to take more time to fill out the questionnaire, but it may also have deterred the individual from completing it all together (Roszkowski & Bean, 1990).

Demographic Variables

There were a number of demographic variables that were collected as a by-product of the study. Although the demographic variables were not specifically used in this research, the data was collected for possible future use, as well as possible additional validity items. The demographic variables included in this study were: gender, education, and age. They were measured as categorical variables, coded as the following:

Gender: Male = 1, Female = 2

Education: No high school degree = 1, High school degree = 2, Bachelor's degree = 3, Master's or higher = 4

Age: Continuous, range from 20-95

Data Analysis

This research had five purposes. Each purpose had a specific statistical procedure to measure its outcome. This section details how each purpose was measured.

Purpose One. Explore the associations among independent risk-assessment variables.

Hanna et al.'s (2008) framework suggests that an individual's risk tolerance, risk

capacity, expectations, and feelings about volatility influence the investment-choice decision. However, little has been done to explore how these variables might be interrelated. The relationships between independent risk variables were investigated using a Pearson correlation coefficient. Preliminary analyses were performed to test for violations of the assumptions of normality, linearity, and homoscedasticity. The results of the correlation analysis illustrated which, if any, of the risk variables were significantly associated with each other.

Purpose Two. Determine if prudent financial risk-assessment goes beyond estimating an individual's risk tolerance.

One of the goals of this study was to assess the degree to which risk profiles might be improved by incorporating risk constructs that are not limited to simply tolerance. Hanna et al.'s (2008) framework suggested four different risk variables in the composition of an individual's investment choice decision-making process. As noted throughout this dissertation, this research uses the constructs from prior literature to help develop a more accurate landscape of the risk-assessment process. Specifically, in addition to risk tolerance, items from the available literature were used to incorporate an individual's risk need, risk perception, risk preference, risk capacity, risk composure, and risk knowledge into the assessment process. Although prior studies have illustrated the importance of multi-dimensional constructs in the risk-assessment process, many current methods of assessments still rely on single-item measures, or profiles that simply assess an individual's risk tolerance. Assessing only an individual's risk tolerance neglects the impact other risk constructs have on an individual's overall risk profile. The second purpose of this study was to see if any of these other risk constructs (in addition to tolerance) had an effect on an individual's profile. Essentially, this purpose was confirmatory in nature. This step was done to confirm that that a multi-dimensional method of assessment is needed to accurately assess an

individual's risk profile. To assess this purpose, an unconstrained Principal Component Analysis (PCA) was conducted on the 14 risk-assessment items (seven risk variables with two questions for each variable). This procedure not only identified what variables contribute to an individual's CRP, but also it grouped the variables into similar factors based on their underlying dimensions. Other studies have utilized the same method in analyzing the factors that contribute to financial risk-profiling (e.g. Grable & Lytton, 1999). The purpose of factor analysis is to reduce and summarize a data set by identifying the underlying, common relationships, and group the variables into factors (Field, 2009; Grable & Lytton, 1999). Further, PCA is an ideal method of analysis when the goal of the research is to reduce data by establishing which components exist within a data set, and how a variable may contribute to that component (Field, 2009). This procedure also eliminated variables from the CRP that did not significantly contribute to the measurement of the CRP's underlying dimensions (Grable & Lytton, 1999).

Factor rotation, or the turning of the reference axes of the factors about the origin, is often used to discriminate among factors. This process assists in interpreting to what degree variables load into the resulting factors. The rotation of the factor axes result in the variables loading maximally onto one factor. That is, this process produces a pattern of loadings on each factor that is as diverse as possible, which makes the data easier to interpret (Field, 2009). The type of factor rotation method depends on whether or not there is good reason to hypothesize that the factors should be correlated with one another. Because it was expected that the various risk-profiling variables would be related to one another, the direct oblin method was selected. This selection of rotation is also consistent with what Field suggests (2009). That is, because this method of factor rotation allows the model's factors to be correlated with one another, the direct oblin approach is appropriate in this study. It was expected that a number of the model's factors

would be correlated with each other.

The PCA procedure isolated the number of components that should be retained in an individual's CRP by grouping the 14 items from the survey into factors. If risk tolerance was the only variable that explained an individual's CRP, then the risk tolerance items would have accounted for the majority of the model's explained variance. If risk tolerance was not the only construct that explained an individual's profile, other risk components should be retained in the analysis. Ideally, the 14 items would have been reduced into seven factors, coinciding with the seven main risk constructs. The results of the factor analysis determined how the 14 risk items should be grouped together, and what the final CRP model should look like.

Purpose Three. Determine the extent to which each risk variable has an impact on an individual's overall risk profile.

Prior financial risk-assessment frameworks (Coleman, 2007; Cordell, 2001; Hanna et al, 2008) have been instrumental in bringing attention to the multidimensional nature of the process. However, little analysis has been done to explore which variables, if any, have more impact on the decision-making process than others. In this study, after the model with the acceptable number of factors was produced, a final PCA was conducted. This constrained procedure included only the variables transformed as a result of the previous factor analysis. Therefore, the analysis showed each factor's explained variance of the model. The results from this procedure provided the weights given to each factor in the risk-assessment process, which determined the impact each factor has on an individual's overall risk profile.

Purpose Four. The development of a comprehensive method of risk-assessment to estimate an individual's overall risk profile.

As a result of the final PCA, a weighted scale was developed which may be used to

determine an individual's CRP score. This step builds upon prior studies involving the risk-assessment process. Prior frameworks and risk-assessment tools (Coleman, 2007; Cordell, 2001; Grable & Lytton, 1999; Hanna et al, 2008) were vital in the development of risk-profiling as a multidimensional process. This research adds to these prior constructs by approximating some experimental weights these dimensions might have on an individual's CRP. It should be noted again that the emphasis of this study is experimental in nature. As with any exploratory study, broad generalizations based solely on the results of this study would not be prudent. Future studies aimed at testing the various constructs of this study, including the weighting each construct has on an individual's CRP, will be necessary to help solidify the validity of the model. The weighted scale developed in this study accounted for the impact that each risk variable has on an individual's overall CRP. The amount of each factor's explained variance on the second PCA model served as the weight given to each factor in the scale. For example, assume after the last PCA is conducted, the first factor explained 25% of the model's variance, the second factor explained 50% of the model's variance, and the final factor explained 25% of the model's variance. As a result, the CRP scale would be weighted so that the first factor contributed to 25% of the respondent's risk profile, the second 50%, and the third 25%. This scale was created in SPSS as a new variable. The resulting scores from the scale were applied as each individual's CRP score.

Purpose Five. The assignment of a measurable outcome to each risk profile score.

After the scale-based CRP score was assigned to each respondent, the scores were applied to a target asset allocation model. To assist in this process, five well-respected researchers and practitioners were assembled as a Delphi group to assign individuals' CRP scores to a measurable outcome.

The Delphi Panel

An expert, or Delphi, panel was utilized in this research to provide a third party, objective opinion in defining appropriate asset allocation ranges, as well as establishing the asset allocation categories. This panel consisted of five industry professionals. Their average experience as practitioners was over 20 years, and all five held either the CFP, CFA, or another industry-related designation. Additionally, one member of the panel held a Ph.D. The experience and objectivity of the panel made for an ideal fit for this part of the research. The group was assembled to (a) provide an industry-oriented opinion of the risk categories (as a measurable outcome), and (b) assign target asset allocation models to each risk category.

The expert panel was tasked with tying the CRP scores to a common measurable outcome in the financial planning field. To do this, target asset allocation models were assigned to each respondent's CRP score. The process of assigning target asset allocation models to a risk profile score has long been the standard measure of applying an individual's risk profile to a measurable outcome. The expert panel was asked to create five target asset allocation categories (i.e., Conservative, Moderately Conservative, Moderate, Moderately Aggressive, and Aggressive). These five asset allocation categories corresponded with how many asset management and financial planning institutions have traditionally, as well as currently, viewed the risk-profiling spectrum (Charles Schwab, 2013a; Merrill Lynch, 2013b; Fidelity, 2013b; Guillemette, et al. 2012). The Delphi group was then responsible for assigning which CRP score ranges should represent each of these asset allocation categories. Again, the purpose of this procedure was to apply the results of the individuals' CRP scores to a measurable outcome within an asset allocation framework. The application of the individuals' CRP scores to an asset allocation model completed the analysis of the comprehensive risk-assessment process in this study.

Reliability and Sample Size Adequacy

Reliability issues play a critical role in the creation and use of instruments designed to predict and measure behavioral attitudes, such as risk-profiling assessments (Babbie, 1983; Davey, 2012; Grable & Lytton, 1999). In this study, as well as any study involving a questionnaire, the survey should consistently reflect the constructs being measured. A scale's reliability helps to explain this consistency. Assessing reliability is especially useful when utilizing factor analysis in scale development. A scale's reliability should consistently reflect the construct it is measuring. This study's model was examined for reliability using the commonly utilized Cronbach's alpha measure (Field, 2009). With this statistic, the data is essentially split into two in every possible way, and the correlation coefficient is computed for each split. The average of these values is the Cronbach's alpha. The theoretical value of alpha varies from 0 to 1, since it is the ratio of these two variances. According to Field, a measure above 0.7 is acceptable. In addition to the scale's overall reliability, Field recommends that the measure should also be applied to subscales within a questionnaire. Therefore, each of the final risk factors was individually subjected to the reliability test as well. This step is needed due to the multidimensional aspect of the CRP. Since one factor does not entirely contribute to the CRP, the reliability measure should be applied to each subscale as well. That is, estimating the reliability of each of the subscales assists in answering the question: *How well does each of the subscale items measure the construct?*

The reliability of the factor analysis procedure is also dependent on the size of the sample. In general, Tabachnick and Fidell (2013) recommend that at least 300 cases are used for a factor analysis. Comrey and Lee (1992) also found that 300 was an adequate sample size for a factor analysis. Determining the adequacy of the sampling size is also an important consideration in the factor analysis procedure. The Kaiser-Meyer-Olkin (KMO) measure verified the sampling

adequacy for the analysis. KMO represents the ratio of the squared correlation between variables to the squared partial correlation between variables. The statistic varies between 0 and 1. A value of 0 indicates that the sum of partial correlations is large relative to the sum of correlations, meaning that there was a large dispersion in the pattern of correlations. This unstable result would mean that a factor analysis is not an appropriate procedure for the data set. A value closer to 1 indicates patterns are more concentrated, and a factor analysis is a suitable method (Field, 2009). According to Kaiser (1974), the KMO statistic should be above the acceptable limit of 0.5.

Chapter 4 - Results

Of the 333 survey samples collected, a final useable data sample consisting of 321 individuals was utilized. The 12 surveys that could not be used had missing or incomplete information, as it related to the 14-item survey. Of the surveys that were incomplete, there was at least one item that was unanswered, or multiple responses were chosen for a given item. For example, the respondent may have chosen two answers for a given question. Or, the respondent may have not answered a question at all. There could have been a number of reasons for the missing or invalid data, although the directions were clear to select only one answer to each item. One reason for the missing data was that the respondent could have been confused by the question, or the individual did not fully understand the item. Although the survey items were borrowed from prior literature, misinterpretation or misunderstanding can still occur with surveys such as the one used in this study. Respondents that provided multiple answers for a given item may have felt that by selecting more than one choice, they were better explaining their preferences. Although the instructions were also specific to mark only one response for each item, a select group of participants still found it necessary to provide multiple responses for a given item. These missing or invalid samples were removed from the data set. This form of dealing with missing data, known as case deletion, is one of the most traditional ways of dealing with missing or invalid data in statistical analysis (Allison, 2001), and was utilized in this research due to its popularity with the statistical analyses performed in the study. Other techniques for dealing with missing data, such as mean substitution, were explored as well. In mean substitution, missing data is simply replaced with the mean score for the item from the dataset. This technique can cause more inaccuracies than case deletion, especially with a sample

of this size (Cole, 2008; Haitovsky, 1968).

The data was collected entirely from (a) a convenience sampling of clients from a financial advisory practice, (b) a neighborhood barbershop, and (c) faculty from two different high schools. The sample collected from the clients of a financial advisory practice was assembled during routine review meetings. Clients were asked if they would like to voluntarily participate. No prizes were offered to this sample. The neighborhood barbershop sample was collected over a three-month period. The barbershop participants were asked about voluntarily completing the surveys while they were waiting for their haircuts. These participants were offered the chance to win gift certificates to local merchants. Each certificate had a \$25 value. The final sample, from the high school faculties, was collected over two different “teacher workdays.” The teachers were asked if they would take the surveys to assist in a university research project. Four \$25 gift certificates were awarded to random participants. The schools were located in the South.

Three basic pieces of demographic data were collected, to assist in describing the sample. The gender distribution was quite even, with 47.4% of the respondents being male, and 52.6% female. Participants’ ages ranged from 20 to 95, with an average age of 57.90 and a standard deviation of 14.84. There was also a mix of the educational background of the respondents. In general, the overall educational level of the participants was quite high, with approximately 85% of the respondents having a bachelor’s degree or higher. Of the participants who had a post-secondary degree, 50.8% of the respondents reported a bachelor’s degree as their highest academic achievement, and 34% of the participants’ highest level of education was a master’s degree or higher. Overall, the sample was well-educated, mature in age, and even in gender disparity. It should be noted again that this study was exploratory in nature. Future studies need

to be done to test the validity and generalizability of the sample, and the models proposed.

Purpose One. Explore the associations among independent risk-assessment variables.

The first purpose of this study was to explore the associations among the various risk-assessment variables. A basic description of the mean and standard deviation scores for each of the 14 items in the survey are shown in Table 4.1.

Table 4.1 Descriptive Statistics of the Independent Risk Variables

Variables	Mean	Standard Deviation	Minimum	Maximum
Risk Tolerance 1	2.16	0.55	1.00	4.00
Risk Tolerance 2	2.05	0.78	1.00	4.00
Risk Perception 1	1.99	0.58	1.00	4.00
Risk Perception 2	1.74	0.80	1.00	4.00
Risk Preference 1	2.07	0.93	1.00	4.00
Risk Preference 2	2.26	0.86	1.00	4.00
Risk Capacity 1	2.86	1.03	1.00	4.00
Risk Capacity 2	2.18	1.20	1.00	4.00
Risk Composure 1	2.74	0.77	1.00	4.00
Risk Composure 2	2.92	0.86	1.00	4.00
Risk Knowledge 1	2.86	1.46	1.00	4.00
Risk Knowledge 2	3.84	0.67	1.00	4.00
Risk Need 1	2.17	0.83	1.00	4.00
Risk Need 2	2.14	0.79	1.00	4.00
Age	57.90	14.84	20.00	95.00
Gender (male=1, female=2)	1.53	0.50	1.00	2.00
Education	2.23	0.76	1.00	4.00

The Correlation Procedure

To gauge the relationships between the items, a correlation procedure was utilized.

Specifically, a bivariate correlation test was implemented in this study. This test examines the strength of association (or relationship) between two variables. Cohen's (1988) insight on effect sizes was used as an objective measure for gauging the strength of the relationships between the variables. Specifically, the following guidelines were used for assessing the relationships:

$r = .10$ (small effect)

$r = .30$ (medium effect)

$r = .50$ (large effect)

Since this purpose of the study was to test for any relationships among variables, significant results of even small effect sizes were considered noteworthy. The results of the correlation procedure can be seen in Table 4.2. Items that had at least a 0.10 (small effect size) correlation with one another, and were statistically significant ($p < .001$), were highlighted in the table.

Several of the variables offered this weak, but statically significant, relationship ($p < .001$) with one another (e.g. RISKPER2 and RISKTOL1, RISKPER2 and RISKTOL2). Several variables had a moderate, or medium, relationship with one another. Significant correlations of at least 0.30 were considered to have this moderate relationship, according to Cohen's assessment of effect sizes. Variables that had relationships of this strength included RISKTOL2 and RISKREF1, as well as RISKCAP2 and RISKNEED1. Additionally, a few of the risk constructs had strong correlations to one another. Cohen defined these relationships as having a correlation of larger than 0.50. The RISKTOL1 and RISKTOL2 variables, as well as the RISKNEED1 and RISKNEED2 items had strong relationships with one another. The results of the correlation analysis indicated that there were some associations among the risk-assessment variables. These relationships, though varying in effect size, helped support the case for further dimension reduction through the use of a factor analysis. This procedure would help simplify the risk-

assessment model, as well as determine the weights each variable should be given in the final CRP scale.

Table 4.2 Independent Risk Variable Correlations

		RISK TOL1	RISK TOL2	RISK PER1	RISK PER2	RISK PREF1	RISK PREF2	RISK CAP1	RISK CAP2	RISK NEED1	RISK NEED2
RISKTOL1	Pearson Correlation	1	.510	.152	.271	.419	.239	.243	.190	.373	.376
	Sig. (2-tailed)		.000	.006	.000	.000	.000	.000	.001	.000	.000
RISKTOL2	Pearson Correlation	.510	1	.022	.236	.365	.080	.230	.075	.301	.330
	Sig. (2-tailed)	.000		.700	.000	.000	.154	.000	.183	.000	.000
RISKPER1	Pearson Correlation	.152	.022	1	-.004	.094	.160	-.075	.033	.041	.133
	Sig. (2-tailed)	.006	.700		.950	.093	.004	.179	.551	.460	.017
RISKPER2	Pearson Correlation	.271	.236	-.004	1	.234	.132	.134	.017	.180	.127
	Sig. (2-tailed)	.000	.000	.950		.000	.018	.016	.759	.001	.022
RISKPREF1	Pearson Correlation	.419	.365	.094	.234	1	.230	.137	-.014	.327	.276
	Sig. (2-tailed)	.000	.000	.093	.000		.000	.014	.801	.000	.000
RISKPREF2	Pearson Correlation	.239	.080	.160	.132	.230	1	.110	-.082	.143	.071
	Sig. (2-tailed)	.000	.154	.004	.018	.000		.048	.144	.010	.204
RISKCAP1	Pearson Correlation	.243	.230	-.075	.134	.137	.110	1	-.230	-.128	-.080
	Sig. (2-tailed)	.000	.000	.179	.016	.014	.048		.000	.021	.155
RISKCAP2	Pearson Correlation	.190	.075	.033	.017	-.014	-.082	-.230	1	.351	.291
	Sig. (2-tailed)	.001	.183	.551	.759	.801	.144	.000		.000	.000
RISKCOMP1	Pearson Correlation	.194	.193	.060	.104	.148	.045	.112	.093	.017	.014
	Sig. (2-tailed)	.000	.001	.283	.064	.008	.426	.046	.094	.767	.798
RISKCOMP2	Pearson Correlation	-.018	.062	.125	.068	.104	.096	.022	-.009	.007	-.070
	Sig. (2-tailed)	.742	.271	.025	.223	.062	.086	.697	.870	.900	.212
RISKKNOWL1	Pearson Correlation	.059	.196	-.008	.060	.058	.024	.174	-.132	-.008	-.032
	Sig. (2-tailed)	.295	.000	.880	.283	.303	.674	.002	.018	.880	.570
RISKKNOWL2	Pearson Correlation	.016	.193	-.148	-.024	.182	-.011	.103	-.010	.099	.077
	Sig. (2-tailed)	.769	.001	.008	.663	.001	.850	.066	.856	.077	.166
RISKNEED1	Pearson Correlation	.373	.301	.041	.180	.327	.143	-.128	.351	1	.669
	Sig. (2-tailed)	.000	.000	.460	.001	.000	.010	.021	.000		.000
RISKNEED2	Pearson Correlation	.376	.330	.133	.127	.276	.071	-.080	.291	.669	1
	Sig. (2-tailed)	.000	.000	.017	.022	.000	.204	.155	.000	.000	

Purpose Two. Determine if prudent financial risk-assessment goes beyond estimating an individual's risk tolerance.

A primary focus of the study was to determine the most effective method of risk assessment. One goal of this research is to determine whether risk tolerance alone is the exclusive metric in an individual's overall risk profile. This part of the study explored other factors that contribute to an individual's CRP. To assess this, all 14 items from the survey were subjected to a Principal Component Analysis (PCA) with direct oblim rotation. This procedure showed which factors contributed to an individual's CRP.

The initial PCA revealed the presence of five components with eigenvalues exceeding 1, explaining 59.04% of the variance. The results from this initial procedure can be seen in Table 4.3. However, the model was not reliable according to Field's (2009) standards.

Table 4.3 Factor Loadings for the Five-Factor Principal Components Solution

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1.					
Item 1	RISKNEED1	0.78			
Item 2	RISKNEED2	0.77			
Item 3	RISKTOL1	0.72			
Item 4	RISKTOL2	0.61			
Item 5	RISKPREF1	0.60			
Item 6	RISKPER2	0.37			
Factor 2.					
Item 7	RISKCAP1		0.69		
Item 8	RISKCAP2		-0.62		
Item 9	RISKPREF2		0.47		
Factor 3.					
Item 10	RISKKNOWL2		-0.82		
Item 11	RISKKNOWL1		-0.43		
Factor 4.					
Item 12	RISKCOMP2			0.79	
Item 13	RISKPER1			0.50	
Factor 5.					
Item 14	RISKCOMP1				0.80

Total Instrument $\alpha = 0.59$

The initial model's Cronbach's alpha was 0.59, below the minimum acceptable alpha for an analysis of this sort. Field (2009) recommends a Cronbach's alpha of 0.70 or higher for a reliable model. Therefore, additional procedures were conducted. Multiple factor analyses were performed sequentially, each time removing the item that contributed the least to the overall

model's reliability. This was done in an attempt to include as many of the original risk variables as possible, but with the most reliable model. For example, removing the RISKKNOWL1 variable increased the model's reliability the most. After this variable was removed from the reliability estimate, the reliability increased to $\alpha = 0.62$. The next item removed was the RISKCAP2 item. This twelve-factor model increased the reliability to $\alpha = 0.64$. Ultimately, this procedure was relinquished once the overall model's reliability met or exceeded $\alpha = 0.70$. When the model's $\alpha = 0.70$, eight of the original fourteen items were retained. This model removed both risk capacity items, both risk composure items, and both risk knowledge items. A discussion of whether the losses of these variables are concerning in any way, and why the factor analysis may have omitted them, are reviewed in the next chapter. Ultimately, one of the purposes of the factor analysis procedure is to reduce variables in a data set into a model that best explains the data. This is precisely what occurred in this step of the research.

A second PCA was then performed on the eight-factor model. This procedure explained 62.49% of the overall model's variance. This is considered to be high, according to Field (2009). The final three-factor, eight-item output can be seen in Table 4.4.

Table 4.4 Factor Loadings for the Three-Factor Principal Components Solution

	Factor 1	Factor 2	Factor 3
Factor 1. RISKNEED			
Item 1 RISKNEED2	.902		
Item 2 RISKNEED1	.832		
Factor 2. RISKPERCEPTION			
Item 3 RISKPER1		.824	
Item 4 RISKPREF2		.663	
Factor 3. RISKTOLERANCE			
Item 5 RISKPER2			-.753
Item 6 RISKTOL2			-.604
Item 7 RISKTOL1			-.573
Item 8 RISKPREF1			-.572
Total Instrument $\alpha = 0.70$			

Interpreting the rationale for how the factors loaded in this procedure was an interesting exercise. The first factor was comprised of both risk need items. This factor was transformed into a new variable, appropriately titled “RISKNEED.” The second factor retained the RISKPER1 item and the RISKPREF2 item. A further description of why these two factors may have been grouped together is addressed in the discussion section of this dissertation. It could be interpreted that the second risk preference item was really how risky an individual *perceived* certain investments to be. Since these items’ similarities involved an individual’s perception of risk, the factor was titled “RISKPERCEPTION.” Last, the third factor grouped both risk tolerance items together, along with the RISKPREF1 item and the RISKPER2 item. This factor loading was the most difficult to interpret, and it is also addressed further in the discussion session. Since both risk

tolerance items were grouped together, and the first risk preference question is often used as a risk tolerance question, it was assumed that one's willingness to take risk was the common theme in this factor loading. Therefore, this factor was transformed into "RISKTOLERANCE." In interpreting the rotated factor pattern, shown in Table 4.4, an item loaded on a factor if the factor loading was equal to or greater than 0.45. Again, the resulting three-factor model consisted of only the eight items from the survey mentioned above, and were transformed into the following three variables: RISKNEED, RISKPERCEPTION, and RISKTOLERANCE.

Risk tolerance was not the only variable that contributed to an individual's risk profile. Had risk tolerance been the only contributor to an individual's CRP, the risk tolerance items would have been reduced as the only factors contributing to the CRP model. This was not the case. The three-factor, multidimensional model is similar to what Kitces finds as an ideal model for comprehensive risk-profiling (Kitces, 2006). In Kitces' model, although the impact of each construct is assumed to be equal in nature, risk capacity, risk perception, and risk tolerance are the three variables that comprise an individual's risk paradigm.

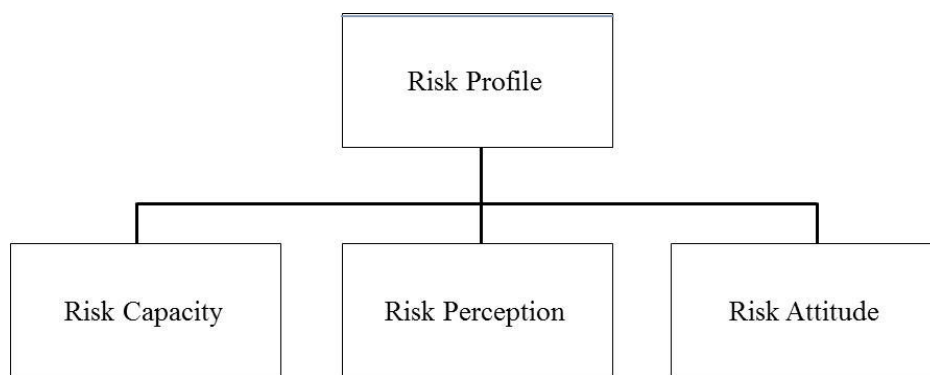


Figure 4.1 Kitces' Paradigm for Evaluating Risk

In a way, the results from this part of the research were confirmatory in nature to Kitces' findings. That is, the financial risk-assessment process is a multidimensional process. The third

purpose of this research discusses the degree to which the risk constructs contributed to an individual's overall CRP and, later, the proper weightings each risk factor should have on an individual's overall risk profile.

Reliability

Researchers recommend that a risk-assessment scale must produce a reliability estimate above $\alpha = 0.6$ to ensure consistency (Grable & Lytton, 1999; MacCrimmon and Wehrung, 1985). The eight-item model had a Cronbach's alpha of 0.70, which would also be considered an acceptable general reliability measure by Field (2009). The reliability estimates for each of the three factors, as well as the overall model, are shown in Table 4.5.

Table 4.5 Reliability Measures for the 8-Factor Model and Individual Factors

Variable	α
Overall 8-Factor Model	0.702
RISKNEED	0.801
RISKPERCEPTION	0.258
RISKTOLERANCE	0.647

Of the three factors, only the RISKNEED item displayed a high reliability measure ($\alpha = 0.80$). RISKTOLERANCE was close to the acceptable minimum reliability standard ($\alpha = 0.65$), and the reliability of the RISKPERCEPTION factor was low ($\alpha = 0.27$). These results were not viewed as problematic. The individual factors were not intended to be used as the distinct measures of risk-assessment, but rather a contribution to the overall model. Again, the reliability of the overall model was $\alpha = 0.70$. Other studies that have examined a multidimensional risk-assessment tool used similar standards to measure the model's reliability, and also had varying reliability results of each individual factor (Grable & Lytton, 1999). Additionally, the Kaiser-

Meyer-Oklín (KMO) value of the overall model was 0.73, which exceeded the minimum acceptable value of 0.50 (Kaiser, 1974). Last, an additional metric was assessed to interpret the factorability of the variables. In theory, in order for a factor analysis to be applicable to a data set, the variables should be somewhat correlated with one another. Otherwise, if the variables were badly correlated with one another (essentially independent from one another), it would not make sense to perform a factor analysis and try to cluster the constructs together. Bartlett's test of sphericity tests for this factorability. If the test reaches statistical significance, it means that the correlations between variables (overall) are significantly different from zero (Field, 2009). The Bartlett's test performed in this part of the study reached statistical significance, supporting the factorability of the risk variables.

Purpose Three. Determine if (and how much) each risk variable has an impact on an individual's overall risk profile.

A final PCA was conducted to estimate the weights each factor should be given in the CRP score. This procedure limited the number of extractions to three (the number of factors produced by the previous procedure), and included only the newly transformed variables (RISKNEED, RISKPERCEPTION, and RISKTOLERANCE). Together, the three factors contributed 100% of the model's explained variance, and provided the exact weights that should be given to each factor in calculating the CRP score. The RISKNEED factor contributed 51.87% of the model's variance, the RISKPERCEPTION component explained approximately 29.57% of the variance, and the RISKTOLERANCE factor explained approximately 18.56% of the variance. The results from this portion of the study are shown in Table 4.6.

Table 4.6 Explained Variance (CRP Scale Weightings) of Each Variable on the CRP Scale, Three-Factor Model

Factor	Explained Variance
Factor 1. RISKNEED	51.87%
Factor 2. RISKPERCEPTION	29.57%
Factor 3. RISKTOLERANCE	18.56%

Purpose Four. The development of a comprehensive method of risk-assessment to estimate an individual's overall risk profile.

The development of a weighted scale was instrumental in fulfilling the purpose of this segment of the study. By creating the scale from the explained variance of the final PCA model, the contribution that each risk item had on an individual's CRP could be assessed. Not only did the constrained PCA determine that each risk variable had an impact on an individual's CRP, but it also showed how much each item affected the individual's CRP.

The CRP Variable

The CRP variable was created by creating a weighted sum of the RISKNEED, RISKPERCEPTION, and RISKTOLERANCE variables. The weighted scale was a function of the respective weights each factor had on the model. That is, the RISKNEED variable accounted for 51.87% of the CRP scale weighting, the RISKPERCEPTION variable accounted for 29.57% of the scale, and the RISKTOLERANCE item accounted for 18.56% of the scale. Each factor's explained variance can be seen in Table 4.6. These variances constitute each factor's weighting in the CRP scale. Based on this weighted model, a CRP scale was developed to determine an individual's risk profile score. Possible CRP scores ranged from a minimum of 2.37, to a maximum of 9.47. The actual scores of the respondents ranged from a minimum of 2.37, to a maximum of 8.60. The mean CRP score of the respondents was 4.98. Basic descriptives of the

CRP scale can be seen in Table 4.7. The assignment of these score ranges to risk profile categories can be seen in Table 4.9, and the process for doing so is explained in the coming sections of the dissertation.

Table 4.7 Descriptive Statistics of the CRP Scale

Variables	Minimum	Maximum	Mean	Standard Deviation
CRP Scores, Possible	2.37	9.47		
CRP Scores, Actual	2.37	8.60	4.98	1.12

CRP Scale Development: The Math

Step One. The scoring of the risk variables.

Each risk item on the risk survey was given a score of 1 to 4, depending on the responses (a through d). The most conservative responses were given a “1,” and the most aggressive responses were assigned a score of “4.” For the risk knowledge items, a correct response was given a “4,” and an incorrect response was awarded a “0.” Specifically, for item 11 (RISKKNOWL1), responses a, c, or d were scored with a “0.” This signified that the response was incorrect. In item 12 (RISKKNOWL2), respondents who chose “a” were given a “0,” indicating an erroneous response. There were a total of 14 items in the original survey. An item-by-item breakdown of each question can be found in Appendix 1.

Step Two. The scoring of the factors.

The risk variables that shared common themes were grouped together by the PCA in this step of the process. The final model consisted of 8 items out of the original 14, reduced into 3 factors. Ultimately, two items made up the RISKNEED (RISKNEED1 & 2) factor, as well as the RISKPERCEPTION (RISKPER1, RISKPERF 2) factor. Four items were grouped into the RISKTOLERANCE factor (RISKTOL1 & 2, RISKPER2, and RISKPERF1). The equation for each transformed variable is shown in Table 4.8. The scores of each transformed variable were a

summation of the items it included. For example, if a respondent scored a “3” for the RISKNEED1 item, and a “2” for the RISKNEED2 item, the individual’s RISKNEED score would have been “5.” The scores from each factor were used in determining the respondent’s CRP score in the next step.

Table 4.8 Variable Transformation, CRP Scale

Variables	Formula Inputted in SPSS
RISKNEED	RISKNEED1 + RISKNEED2
RISKPERCEPTION	RISKPER1 + RISKPER2
RISKTOLERANCE	RISKTOL + RISKTOL2 + RISKPER2 + RISKPER1

Step Three. The scoring of the CRP scale.

After the factors were transformed into the new variables in SPSS, and scores were assigned to each of the new items, the CRP scale could be formed. The CRP scale was simply a weighted summation of the three factors. Specifically, the equation was the following:

$$CRP\ scale = (RISKNEED * 0.52) + (RISKPERCEPTION * 0.30) + (RISKTOLERANCE * 0.18)$$

For the respondents, this newly transformed variable reflected the summated, weighted score of their risk profile. With this measure, individuals’ risk profiles could be applied to a measurable outcome for financial planning purposes.

Purpose Five. The assignment of a measurable outcome to each risk profile score.

The final purpose of the study was to assign an individual’s risk profile score to a measurable framework within the field of financial planning. An expert panel was assembled to assist in this part of the research.

The Delphi group was responsible for the two main procedures mentioned above. First, the expert panel was tasked with assigning the CRP score ranges of the respondents to the appropriate risk profile category (e.g., conservative, moderate). This was done by assigning

possible CRP score ranges to a corresponding category. To do this, possible CRP scores were split into five equal groups. Subsequently, each risk category was applied to the CRP score range in order of increasing risk. For example, the lowest score range was applied to the conservative profile, the next range was given the moderately conservative profile, etc. Second, the committee was responsible for developing the target asset allocation models that corresponded with each risk profile category. As noted earlier, the process of assigning target asset allocation models to a risk profile score has long been the standard measure of applying an individual's risk profile to a measurable outcome. Five asset allocation categories were selected to coincide with each of the five risk profiles. These risk categories (conservative, moderately conservative, moderate, moderately aggressive, and aggressive) correlate with how many asset management and financial planning institutions have traditionally, as well as currently, viewed the risk-profiling spectrum (Merrill Lynch, 2013b; Guillemette, et al., 2012; Morgan Stanley, 2013; Wells Fargo, 2013a). The Delphi panel determined that these five categories were applicable to this research as well. The average CRP score was 4.98, with a standard deviation of 1.12, and a range of 2.37 to 8.60. Overall, 14.3% of the respondents were classified as having a conservative CRP. The majority of the participants were classified as having either a moderately conservative (47.9%) or moderate (31.8%) risk profile. Last, 4.4% of the respondents were classified as having a moderately aggressive CRP, and only 1.6% of the sample was characterized as aggressive. These results were consistent with distributions of financial risk-assessment scores found in the literature (Grable & Lytton, 1999; MacCrimmon & Wehrung, 1985). The CRP score ranges and the corresponding risk profile categories and asset allocation models for the respondents are shown in Table 4.9.

Table 4.9 CRP Scores, Categories, and Asset Allocation Models

CRP Score Range	Risk Profile Category	Target Asset Allocation
2.37-3.79	Conservative	20% stocks, 55% bonds, 25% cash
3.80-5.21	Moderately Conservative	40% stocks, 50% bonds, 10% cash
5.22-6.63	Moderate	60% stocks, 35% bonds, 5% cash
6.64-8.05	Moderately Aggressive	70% stocks, 25% bonds, 5% cash
8.06-9.47	Aggressive	80% stocks, 15% bonds, 5% cash

The second step in this process, after assigning CRP scores to the five risk profiling categories, was to determine the asset allocation of each risk profile. That is, the Delphi group also determined the acceptable asset allocation for each risk profile. The asset mixes that the Delphi group determined as acceptable asset allocation ranges for each risk profile category can also be seen in Table 4.9.

The application of an individual's CRP score to the appropriate asset allocation completed the risk-assessment process for this study. In this step, an individual's risk profile was tied to a measurable outcome in the financial planning process. As with any exploratory study, further testing is encouraged to increase the validity and generalizability of this model. Additionally, it is important to note that this step should never serve as the sole initial stage of the financial planning process. That is, risk-assessment is not the only component of the primary stages of the financial evaluation process. Comprehensive risk-evaluation should be conducted alongside a thorough examination of an individual's goals, needs, and objectives to accurately arrive at the most prudent financial plan. As a reminder, the focus of this study was on comprehensive financial risk-evaluation. However, this step should be used in conjunction with other important stages in the financial planning process, such as an individual's personal values, goals, life and current situation, and any economic factors, to achieve the best financial planning

results (FPA, 2013).

Validity Item

The last step in the study involved the test of validity. As discussed in the previous chapter, this test was conducted by examining the instrument's construct validity. Again, testing the validity determines the extent to which one can be sure the measure represented an individual's risk profile (Grable & Lytton, 1999; Litwin, 1995; Silva, 1993). In addition to the 14-items in the risk profile questionnaire, respondents answered the single-item assessment presented in the previous chapter. Respondents were asked to answer a risk-assessment item utilized by the Rutgers University investment risk tolerance quiz (njaes.rutgers.edu/money/riskquiz, 2013). Content validity was tested using this single-item measure. The question read:

In general, how would your best friend describe you as a risk taker?

- a. A real gambler*
- b. Willing to take risks after completing adequate research*
- c. Cautious*
- d. A real risk avoider*

The responses to this item were used to validate the CRP score developed as a result of the study. Responses to this validity question are known to be associated with an individual's investment allocation towards risky investments. Theoretically, a higher risk score on an individual's CRP should have been associated with a higher score on the validity item. The SCF question is widely used as a proxy for risk-assessment, especially in a single-item validity procedure. However, because the item was used as one of the two questions involving risk tolerance in this study, the SCF item would not be an ideal selection in testing validity. The Rutgers University item was selected due to its comprehensive nature, yet single-item format. Although assessing validity was

an instrumental step in the dissertation, doing so was not meant to detract from the study in any way. Had a lengthier validity item been used, responses in the data collection process may have been weaker. Additionally, other studies (Grable & Schumm, 2007) found the question useful in assessing an individual's general risk-taking behavior. Again, the question was not meant to serve as the most accurate, comprehensive measure of an individual's risk profile, but rather serve as a measure to help substantiate the validity of the comprehensive assessment done in this study.

A correlation procedure was conducted to assess the relationship between the validity item and an individual's CRP score. The analysis revealed a significant correlation coefficient of 0.43 ($p < 0.001$). The size of this relationship is considered to be moderate (Field, 2009; Pallant, 2007). Although a single-item measure does not fully encompass the wide spectrum of the financial risk-profiling process used in this study, a significant correlation to the CRP provides validity to the scale. Additionally, the positive, moderate correlation between the CRP score and the single-measure validity item indicated that there is construct validity with the multidimensional scale. Although both measures are gauging an individual's risk profile, it should not be a surprise that the multidimensional assessment is not strongly correlated to the single-item measure. The CRP scale's encompassing nature takes aspects into consideration that the single-item method does not. Grable and Lytton (1999) had similar results when they subjected their lengthier assessment of 13 items to a single-item validity procedure. In summary, the assessment of validity supported the potential applicability of the instrument.

Chapter 5 - Discussion

Purpose One. Explore the associations among independent risk-assessment variables.

The results from the first purpose of the study were promising. There were several associations among the risk-profiling variables. The correlation analysis yielded several variables that were highly correlated with one another, at significant levels. This procedure, though simple, was key in determining which risk-profiling variables had the most significant associations with one another. For example, both risk tolerance items were highly correlated with each other, as were both risk need items. The appearance of several correlated variables was a key element in being able to explore the data further through the use of factor analysis.

Correlations/Relationships among Variables

The correlation procedure completed at the initial stage of data analysis revealed some intriguing results. First, it is worth noting that the first and second risk capacity items had a negative correlation with one another. This meant that the longer individuals' time horizons, the lower their financial strength (as judged by the items comprised by the RiskCapacity2 variable). This was consistent with the Life Cycle Hypothesis (Modigliani & Ando, 1963), which states that individuals build wealth (and become more financially sound) the older they become. Next, it could be hypothesized that each item within a risk category would be highly correlated with one another. For example, one could assume that the first risk capacity item would correlate highly with the second risk capacity item, and this trend would continue across all of the risk variables. Although this was the case with certain items (both risk tolerance items and both risk need items), it was not the result in every scenario. Table 4.2 shows the results of the correlation procedure.

A discussion of how and why items may have been grouped together is addressed in

more detail later in this chapter. However, the correlation procedure indicated some intriguing initial relationships among the risk variables. For example, the first risk tolerance item did not only correlate with the second risk tolerance item, but it also had a significant relationship to the first risk preference item ($r = 0.42, p < .001$). One possible interpretation of why the risk tolerance items and the first risk perception showed a moderate relationship could be that the constructs deal with an individual's subjective, pre-risk engagement behavior. That is, an individual's willingness to take risk and an individual's preference to take the risk both have to do with the individual making subjective judgments on the risk behavior before (or without) actually engaging in the behavior. Further, the risk tolerance items had significant relationships with each of the other constructs. The strength of the associations varied, but these relationships were noteworthy. Although the RISKTOLERANCE CRP variable contributed less than 20% to the overall model's score, the risk tolerance items were the only variables to have associations of significance with all of the other items. This finding could be taken at face value, and understood to be a simple association of one variable to the others. Or, the relationship that the risk tolerance items had with the other variables may have a deeper meaning. For example, is it possible that the risk tolerance items were somehow captured (in part) in some of the other variables? Are the risk tolerance constructs, when viewed by themselves, more powerful than at first glance due to their relationships with all of the other variables? Certainly the risk need items had the largest impact on an individual's CRP. However, the broad correlation of the risk tolerance items with the other variables sheds some light on single-item methods of assessment, and perhaps the risk tolerance construct is used often in these one-dimensional profiles. That is, single-item measures that solely assess the risk tolerance construct may be isolating the one variable that covers the widest spectrum of the risk-assessment landscape. Based on the results of this study, single-item

methods of assessment do not fully integrate the comprehensive nature of the risk-profiling process. Still, the broad relationship that the risk tolerance items had with the other variables suggests why other methods of assessment isolate that one construct.

There were other relationships that were noteworthy as a result of the correlation procedure. The first risk need item and the second risk capacity item (moderately correlated with one another, $r = 0.35$, $p < .001$) deal with an individual's objective measures of financial risk. These constructs involve the individual assessing how much risk needs to be taken with respect to the financial plan, or how much risk the financial plan can withstand. Neither situation is subjective in nature. With risk need, there is either a need to take risk or not. With risk capacity, individuals either have the ability to withstand risk or they do not. It is possible that these relationships exist because the variables were either subjective or objective. The similarities discovered in this part of the study were not only insightful, but also encouraging for the future steps in this study. The significant correlations among the risk constructs made the factor analysis methodology appropriate for assessing the relationships further and reducing the data into similar groupings. Follow up studies will be instrumental in describing the factors' similarities further, in addition to enhancing the reliability and validity of the model.

Purpose Two. Determine if prudent financial risk-assessment goes beyond estimating an individual's risk tolerance.

The results of this portion of the study helped to explain the comprehensive nature of the financial risk-assessment process. The PCA identified three factors that contributed to an individual's Comprehensive Risk Profile (CRP). The factors produced from the PCA suggest that the risk-assessment process is a multidimensional procedure. Because of this result, risk tolerance should not be the only item considered when evaluating an individual's risk profile.

Therefore, assessments that only take into account an individual's risk tolerance are incomplete. That is, one risk construct cannot possibly assess an individual's financial risk profile adequately. This finding is significant, and it helps explain the second purpose of the study, which was to determine if risk tolerance is the only factor in assessing an individual's risk profile. One-dimensional assessments of financial risk neglect to incorporate other factors (e.g., risk need or risk perception) that contribute to an individual's risk profile. Other studies that tested single measures of financial risk-assessment, relative to multidimensional constructs, had similar findings (Barsky, Juster, Kimball, & Shapiro, 1997; Grable & Lytton, 1999; Hanna & Lindamood, 2004; Kitces, 2006).

As noted from the results, a factor analysis grouped the items from the survey into three distinct variables. These items were reduced into their assigned groups due to the inherent similarities that each risk variable had with one another. A review of these factor loadings is seen in Table 4.4. This section of the paper will attempt to explain the rationale for why the items may have been reduced into their corresponding groups.

The RISKNEED Variable

The rationale for how the RISKNEED factor loaded the way it did was perhaps the most obvious of the three new variables that were created as a result of the PCA. First, both of the risk need items were part of the original risk need category. Additionally, both items were objective in nature. Further, both risk need items were similar in content. Although the first risk need item pertained to an individual's primary financial goal, and the second item related to the individual's secondary goal, the content of each question was essentially the same. Perhaps one of the more surprising results from this factor was the amount of explained variance this item contributed to the overall model. The RISKNEED variable explained 35.17% of the model's

variance by itself. This is noteworthy, as the RISKNEED item explained more of the model's variance than the other two variables combined. A further explanation of why this finding is significant in today's financial planning environment is addressed later in the chapter.

The RISKPERCEPTION Variable

The second variable formed as a result of the factor analysis was the risk perception variable. RISKPERCEPTION included the first risk perception item and the second risk preference variable. At first glance, one may assume this is difficult to explain. However, after reviewing each item in more detail, the factor loadings for this grouping should not be a surprise. Upon further review, the first risk perception question can clearly be understood as an item pertaining to one's view of risk. It specifically asks:

When you think of the word "risk," which of the following comes to mind first?

- a. Loss*
- b. Uncertainty*
- c. Opportunity*
- d. Thrill*

Because of the subjective angle of the question, one which specifically addresses an individual's view on the subject of risk, the classification of this item as one's perception of risk is understandable. What may be more difficult to interpret is why the second risk preference item was grouped together with this item. The question from the survey read as follows:

Suppose a relative left you an inheritance of \$100,000, stipulating in the will that you had to invest all of the money into one of the following choices. Which one would you prefer?

- a. A savings account or money market mutual fund*
- b. A mutual fund that owns stocks and bonds*

c. A portfolio of 15 common stocks

d. Commodities like gold, silver, and oil

It is possible that this question involved individuals' perception of risk, rather than their preference. For example, it is possible that the respondent viewed (or perceived) investments such as commodities as less risky than a mutual fund that owns stocks and bonds. Statistically, a portfolio of stocks is less risky than a basket of commodities. However, it is possible that respondents did not subjectively view these choices "correctly." Some individuals may perceive gold as more conservative than a portfolio of stocks. This being the case, the second risk preference item is really more comparable with a risk perception item. Therefore, not surprisingly, the item was grouped together with another risk perception variable in the factor analysis. The RISKPERCEPTION variable explained 14.12% of the overall model's variance.

The RISKTOLERANCE Variable

The RISKTOLERANCE variable was formed as a result of both risk tolerance items, the first risk preference item, and the second risk perception item being grouped together by the factor analysis. Both risk tolerance items had an inherent similarity in that both items clearly involved an individual's willingness to take risk. The loading of the first risk preference item and the second risk perception item took a deeper analysis. The first risk preference item read the following:

Assume you had a portfolio with a balance of \$100,000. Given the best and worst case returns of the four investment choices below, which would you prefer over the course of a one-year period?

a. \$10,000 gain best case; \$0 loss worst case; \$4,500 gain average case

b. \$18,000 gain best case; \$12,000 loss worst case; \$6,000 gain average case

c. \$26,000 gain best case; \$18,000 loss worst case; \$8,000 gain average case

d. \$35,000 gain best case; \$30,000 loss worst case; \$12,000 gain average case

Although the question clearly uses the word “prefer” to isolate the subjective *preference* of an individual to take risk, this question has been used by risk questionnaires to assess an individual’s *willingness* to take risk. The question is seen in some variety in several risk surveys industry-wide (Merrill Lynch, 2013a, Charles Schwab, 2013b, Fidelity, 2013a & b; Guillemette, Finke, & Gilliam, 2012). Additionally, the item bore a striking resemblance to the second risk tolerance item. Therefore, it should not be a surprise that this item is reduced into a factor that includes both items. Although the word “preference” is used in this study’s version of the question, the content of the item may be more fitting of individuals’ willingness to engage in risk, as opposed to their preference. It is possible that the respondents viewed this question as a subjective assessment with respect to this willingness.

The second risk perception item was also reduced to the RISKTOLERANCE variable.

This question read:

Assume that your financial plan is statistically likely to fail. Which of the following actions would you perceive as the most appropriate way to increase the likelihood of your financial plan’s success?

a. Lowering your future expectations

b. Saving more

c. Selling assets

d. Taking on more risk with your investments

Although the word “perceive” is used in the framing of this question, it is likely that the item was grouped in this factor because of its similarity to the other risk tolerance variables. That is, the

main trait that the second risk perception item had in common with the other variables that loaded into this factor was individuals' subjective willingness to engage in future financial risk. In this scenario, the respondent has the choice of how willing they are to take part in various scenarios, all of which bare varying levels of financial risk.

Essentially, the loadings of these items into the same group illustrated that there were commonalities among the variables. Perhaps a more appropriate title for the variable would be "FUTURE RISK TOLERANCE," or an individual's future willingness to engage in risk, due to each item containing a hypothetical future scenario in which the respondent had a subjective choice involving making a risky decision at some point in the future. However, the similarity among the variables assumed in this research was an individual's subjective willingness to engage in risk. Therefore, the transformed variable was simply titled "RISKTOLERANCE."

Kitces (2006) had similar thoughts on what factors should comprise an individual's risk profile. His hypothetical framework, shown in Figure 4.1, includes risk capacity, risk perception, and risk tolerance. This three-factor model is extremely comparable to the three-item result of the factor analysis conducted in this research. In fact, as discussed below, it is possible that the risk capacity item and the risk need variable are redundant, and this is why the risk need variable was retained in this study (and the risk capacity item was not). Kitces' model adds to the validity of the model developed as a result of the second purpose of this study. The next step in this research extended upon Kitces' framework by determining the impact that each of the three constructs had on an individual's CRP.

It is important to discuss the items that were removed from the model as a result of the factor analysis, possible reasons that they were not included, and the impact that the removal of these items could have on the research.

Risk Capacity

By definition, risk capacity and risk need are different. However, it is possible that some of the properties in risk capacity were present in the risk need construct. Therefore, perhaps the risk capacity construct was redundant in the model, causing the factor analysis to remove the variable. There were similarities in structure between the capacity questions and the risk need items. That is, an individual's risk capacity may have been captured in the respondent's need to take risk in order to accomplish a financial goal. This is difficult to know for sure from this exploratory study, but it is possible that the risk capacity item was simply redundant, and therefore the risk need variable was retained in its place. Additionally, both of the variables are objective in nature. That is, an individual with a high risk need must incur financial risk to accomplish a given goal. Similarly, an individual with a high risk capacity has the financial ability to withstand risk. Neither situation is a choice, but a defined financial condition. In future studies, it would be worthwhile to see if the risk capacity and risk need items can be used interchangeably for modeling purposes, or if one construct is retained in place of the other. Kitces' (2006) model, which incorporates risk capacity, should also be revisited and tested with the risk need construct. Future studies aimed at providing validity to the model proposed in this research, as well as Kitces' framework, will help confirm the relationship between the risk capacity and risk need variables, and determine if risk capacity continues to be omitted in the factor analysis process. The removal of the risk capacity item was necessary in this research, but it should be tested in future research to test the validity of this result.

Risk Composure

This variable is new to the financial risk-modeling process. Therefore, it may not have been a surprise that the construct was retained by the factor analysis. This item was likely removed from the model because it lacked enough of an impact to be retained by the factor

analysis. The variable could still be quite useful for advisors. Perhaps this construct could still serve as a “qualitative” aspect of the risk-assessment process. Knowing how a client is going to react in the presence of risk is still a valuable insight to a planner, even if it cannot quite be quantified as a result of this study. Setting the right expectations, and being able to caution those who have a low risk composure could be instrumental in the client/advisor relationship, and also help keep a prudent financial plan on track during periods of volatility. Future tests of the model presented in this research should confirm whether or not the risk composure construct can be quantified into a financial risk-assessment model.

Risk Knowledge

Similar to the risk composure construct, the risk knowledge variable was omitted as a result of the factor analysis, and unlikely had properties that were found in other variables. In other words, redundancy can probably not be blamed for the removal of the risk knowledge construct. However, like with risk composure, assessing this aspect can be insightful for the advisor as well. Knowing a client should include understanding the knowledge the individual demonstrates with respect to financial risk. Grasping this trait will also help practitioners to better assist their clients and to articulate various aspects of the financial planning process.

Risk Preference

Although risk preference was technically not retained as an individual factor, both risk preference items were incorporated into two of the other factors. As mentioned in the results, the first risk preference item was factored into the RISKTOLERANCE construct. The second risk preference item was grouped into the RISKPERCEPTION factor. These pairings made sense. The first risk preference item is one that is commonly used as a single-item risk tolerance measure, although it uses the word “prefer” in the question. It is highly possible that the

construct is really testing one's willingness to engage in risk. The second risk preference item tapped into an individual's perception by asking which type of investments the respondent preferred. This also tests the individual's perception of how each choice is viewed, or perceived, in terms of risk.

Overall, the factors that the model retained, and the items that the factor analysis omitted, made logical sense. One of the purposes of any factor analysis is to reduce data, and this is exactly what occurred as a result of the procedure in this study. Ultimately, the factors that were retained were reasonable, and the manner in which they were reduced was also rational. Rationale regarding why the omitted items were removed from the model could be explained, although future tests are needed to add validity to the model's retained factors. The results from the second step of this research illustrated that financial risk-assessment goes beyond estimating an individual's willingness to take risk.

Purpose Three. Determine if each risk variable has an impact on an individual's overall risk profile.

The results from this portion of the study were also promising. Specifically, the extent to which each factor contributed to an individual's risk profile was uncovered. The final, constrained PCA revealed each factor's contribution to an individual's CRP. The impact of this outcome was far-reaching. Not only were multiple variables (in addition to risk tolerance) found to contribute to an individual's risk profile, but each factor's impact on the individual's CRP could also be assessed. This is a significant finding. Studies that have explored the impact of multidimensional risk constructs on an individual's CRP are scarce. The results from this part of the dissertation add to the limited research involving the impact of various risk constructs on an individual's comprehensive profile. The amount that each risk construct contributed to an

individual's overall CRP was identified through the final PCA. Utilizing these values, a scale could be created that accurately weighted each risk factor (according to its explained variance). Table 4.6 shows the explained variance, or weighting, each of the transformed variables had on the overall CRP model. Again, these weightings determined the impact that each of the transformed variables had on an individual's CRP. The varying contributions each factor had on the model suggested that (1) one-dimensional assessments of an individual's financial risk profile are inadequate and (2) risk constructs have varying levels of impact on an individual's overall financial risk profile. Based on these findings, financial risk-assessment instruments that assume each item has an equal impact on an individual's overall risk profile are flawed. This is significant because nearly all financial risk-assessment profiling instruments weight the constructs equally (Bright & Adams, 2000; Grable, Archuleta, & Nazarinia, 2010; Grable & Lytton, 1999). The results found in this study indicate that this is an extremely detrimental error in the evaluation process. The factor analysis procedure in this study explained that financial risk-assessments need to be multidimensional, but they should also be weighted relative to the importance each construct has on the overall model. The weightings applied in this research were used to form the CRP scale in the fourth purpose.

Purpose Four. The development of a comprehensive method of risk-assessment to estimate an individual's overall risk profile.

After determining the adequate impact each risk construct had on an individual's CRP, the weighted scale was developed to quantify an individual's financial risk profile. A risk-assessment scale that weights each risk variable based on its impact on the overall model is rare, and seemingly scarce among the financial risk tolerance literature. Based on this study's results, an equally weighted model is not the most accurate method in calculating an individual's overall

risk profile due to the varying impacts that each variable had on an individual's CRP.

The CRP Scale

The final items included in the CRP scale, and the resulting weights given to each variable, warrant some discussion. First, it is important to note that not all of the original items were included in the CRP scale. This is because the dimension-reducing procedure abridged the number of factors to three, which included a total of eight items from the original fourteen-question assessment. None of the original risk capacity, risk composure, or risk knowledge items was included in the final model. This does not mean that these aspects are unimportant to financial advisors. Knowing how a client behaves in the presence of a risk situation (risk composure) is certainly valuable for an advisor to understand. However, the factor analysis failed to include these variables, as well as an individual's knowledge of risk and capacity to take risk. The elimination of variables is common in a factor analysis procedure (Field, 2009), and this was also the case in this study.

It is worth discussing the variables that were retained as a result of the factor analysis. The RISKNEED variable had the most dominant weighting (52%) in the CRP scale. This is significant for a number of reasons. First, it may be surprising that one variable constituted over half of the entire scale's weighting. Next, RISKNEED'S contribution to the scale meant that an objective variable affected the respondents' risk profile. Specifically, it meant that roughly half of an individual's risk profile was made up of objective factors, and half of subjective factors. This contributes to the financial risk-assessment literature significantly. The retention of the RISKNEED variable, in addition to the RISKTOLERANCE and RISKPERCEPTION variables, confirms that both subjective and objective variables are needed to accurately assess an individual's risk profile. This is consistent with results from other studies

that involved assessing subjective and objective measures in the risk-assessment process (Adkins, 1997; Hanna et al., 2001; Hanna & Chen, 1997). Future studies will tell if the weightings proposed in this study remain the same throughout other data sets and sample sizes. In order for the CRP scale to be generalizable, it is imperative that the scale factor weightings remain consistent across future replication studies.

The large impact of the RISKNEED variable also has implications for “Goals-Based” financial advisors and planners. Goals-based wealth management involves aligning individuals’ financial planning with their personal, behavioral, and financial goals (Brunel, 2012). This method of financial planning and wealth management has received a lot of positive attention in the post-financial crisis era. This process allows advisors to better relate financial advice to their clients’ behavior, and is becoming the norm for new-age financial practitioners and thinkers (Chharbra, 2005; Chhabra et al., 2008; Nevins, 2004; Pompian, 2006). Many financial institutions are beginning to adopt the process as the norm for their wealth management process (Brunel, 2012; Merrill Lynch, 2013c; Wells Fargo, 2013b). Although this method of wealth management aligns individuals’ goals with a financial planning process, it does little to account for risk profiling. That is, although a wealth management plan can be structured through the goals-based planning process, an individual’s risk profile is often an afterthought. This could be dangerous for financial advisors. Regardless of how well a goals-based wealth management plan is designed, individuals could abandon the process if it bares more risk than they are comfortable taking. Perhaps one of the reasons risk is not accounted for adequately in goals-based planning is because goals-based wealth management is an objective process. It involves aligning individuals’ goals with their financial plan. Incorporating an objective factor in the risk-assessment process coincides with the principles of goals-based wealth management. That is, goals-based planning is

needs based, and the CRP scale formed as a result of this study incorporates an individual's need to take risk. The CRP scale designed in this study accounts for an individual's need to take risk. This should prove noteworthy for financial advisors who utilize the goals-based planning model. Not only can advisors align and relate their clients' behavior and goals to a financial plan, but practitioners can also take objective risk factors (e.g. risk need) into consideration when forming plans. This necessary step will not detract from the goals-based planning process, but it will enhance the client experience by taking an individual's risk profile into consideration when advisors make recommendations. This way, a client will not be as likely to desert an otherwise sound financial plan because it is too risky for them to adhere to.

Understanding an individual's perception of risk was clearly an important facet of the risk profile as well. Risk perception constituted 30% of the CRP scale's weighting; however, it is a rarely seen construct in current methods of financial risk-assessment. An individual's subjective view of risk affected the overall CRP model. Advisors and researchers can learn from this finding as well. Not only is it important that practitioners understand their clients' objective need to take risk, but advisors also need to comprehend how their clients view risk. Realizing how individuals identify risk is vital to the planning process. For example, although commodities are statistically a riskier asset than a basket of stocks, some individuals may perceive the hard assets as a less risky selection. Similarly, some clients may view risk as an opportunity, whereas others view it as a potential for loss. Absorbing these viewpoints into a financial risk profile is critical in making an accurate assessment. Ultimately, the results of this study found that risk perception is an integral part of the CRP process.

Last, an individual's willingness to take risk was an integral component of the final model as well. Risk tolerance was a driving force in the composition of the CRP scale, but it only

accounted for 18% of the overall model's weight. Although the respondent's willingness to take risk at some point in the future was an important part of the risk-assessment process, risk tolerance had a rather small contribution to the overall CRP. This is a notable finding. Surveys of risk-assessment that isolate an individual's willingness to take risk may be ignoring other, more impactful, aspects of the profile. Quantitatively speaking, assessments that only assess an individual's future willingness to engage in risk are missing over 80% of the risk-profiling picture.

The results of this study, and the valid formulation of a multidimensional risk instrument, should continue to raise questions as to how current methods of financial risk-assessment tools are designed. If an individual's risk profile is multidimensional (and the results from this research indicate this), a unilateral weighting to an assessment should not be acceptable. Specifically, an individual's financial risk profile is not one-dimensional, so the method of assessment should not be one-dimensional. Additionally, the risk-profiling tool should also accurately weight the impact of each variable on the individual's overall profile when determining an overall risk-profiling score. Overall, the three-factor model developed in this research takes into consideration individuals' objective risk need, subjective willingness to incur risk in the future, and their view of how they define risk. These distinct and imperative components define what factors should be considered when estimating an individual's financial risk profile. The scale developed as a result of the factor analysis explained how much weight each factor should be given in the CRP scale.

Purpose Five. The assignment of a measurable outcome to each risk profile score.

The application of target asset allocation models to an individual's CRP score completed the risk-assessment process in this study. The assignment of an individual's CRP score to an

asset allocation model connects the results of this research to a commonly accepted measurable outcome within the field of financial planning. This step in the research was vital in providing an outcome to the multidimensional financial risk-assessment process. As a result of the findings from the study, the factor analysis, and the contribution each factor had on the overall CRP model, a revised empirical model was developed. This model, shown in Figure 5.1, reflects the weighted, three-factor financial risk-profiling framework, and the connection of this model to an individual's target asset allocation model. This model serves as the study's updated empirical model, based on the results from the research. The framework shows the three factors retained as a result of the factor analysis. Additionally, each construct is weighted relative to the contribution each variable had on an individual's CRP. It is hoped that this framework shall serve as the model for any financial risk-assessment procedure.

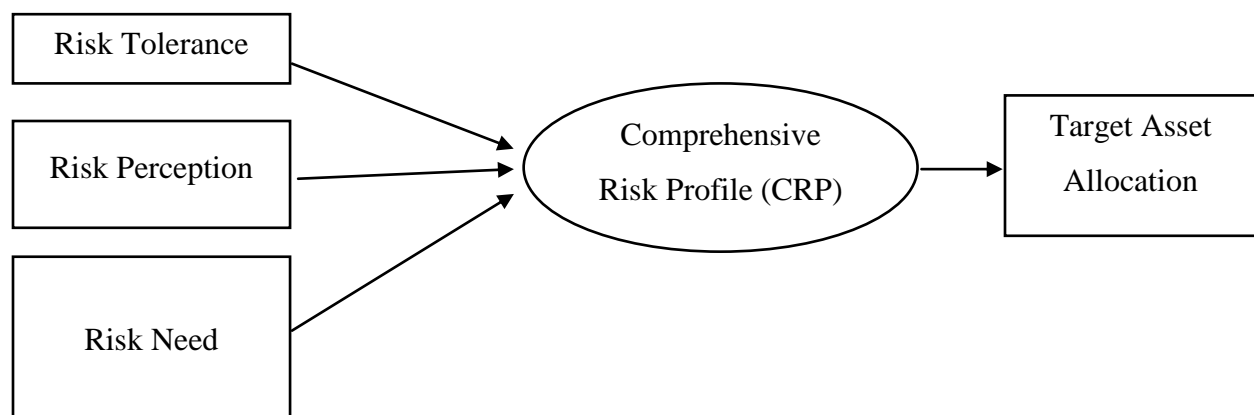


Figure 5.1 The Framework for the Comprehensive Risk Profile

Comparison of the Final Empirical Model to the Hypothesized Framework

The final empirical model differed from the hypothesized conceptualization. This was a result of the final model including three factors, instead of the original proposed seven. Some of these items were captured in the final three constructs. For example, the second risk preference item was grouped into the RISKNEED factor. The first risk preference item was reduced into the

RISKTOLERANCE construct. Other items, such as the risk capacity variables, may have influenced the factors in some way (RISKNEED), although these items were not specifically included in the final model. Although it is difficult to assess from this study, it is entirely possible that some of the items that were omitted from the factor analysis had an effect on the final empirical model. Another difference between the final model and the original framework is that not all of the constructs contributed equally to an individual's CRP. The original conceptualization assumed a null hypothesis, as the weights of the variables were unknown. The final model reflected the impact that each construct had on the CRP. Ultimately, the final three-factor model is both different in appearance and structure from the hypothesized model.¹

Comparison of the Final Empirical Model to the Conceptual Frameworks

It is important to note how the final empirical model related to the original frameworks that guided this study. Specifically, a discussion of how the results of this research fit into Hanna et al.'s (2008) model is warranted. First, it is noteworthy that the results from this study showed that the risk-assessment process is multidimensional in nature. Hanna et al.'s risk-profiling model found this to be the case. Next, the factors produced as a result of the PCA revealed strikingly similar comparisons to the constructs suggested by Hanna et al. Risk tolerance was one of the variables included in the risk profile of the conceptual model. One's willingness to engage in risk was also a variable in the CRP model of this study. Additionally, an individual's feelings were an aspect of Hanna et al.'s model. Both risk preference items were retained in the final CRP model as well. This showed that, although the risk preference items were reduced into other factors, an individual's subjective feelings about risk were taken into consideration with the CRP model. Further, it appeared that the risk perception construct was present in both the conceptual model, as well as in the final empirical model. Hanna et al. included the "expectations" construct

in their framework. Since perception was defined as an individual's subjective view of risk, it can be assumed that one's expectations are a part of this process. Last, although the empirical model found risk need to be a large driver of the CRP, and Hanna et al. found risk capacity to be a construct of their model, the connection is worth discussing. Earlier sections of this dissertation have addressed the connection between risk capacity and risk need. Both are objective in nature, and they each address an individual's financial ability to some degree. So, although the models appear to deviate with regard to these constructs, there are some inherent connections present. Future studies to test Hanna et al.'s model with the framework proposed in this study would be worthwhile. Additionally, as noted in earlier sections, replication studies would also help clarify the risk capacity construct, and the impact it has on the CRP. Nonetheless, there is an objective risk construct in both the model proposed in this study (risk need), as well as Hanna et al.'s framework (risk capacity).

Ultimately, the empirical model did not deviate dramatically from the conceptual model. Based on the results from this research, the conceptual model selected for this study appeared to be an extremely ideal fit to guide the research. However, this research was meant to be an extension of Hanna et al.'s model. Additional constructs (risk perception, risk preference, risk composure, risk knowledge, and risk need) were all tested, in addition to risk tolerance and risk capacity, to determine an optimal CRP. Additionally, this study extended upon Hanna et al.'s framework, and many other studies that explore the risk-assessment process, by determining the optimal weights of the constructs applied to the CRP model. The conceptual framework assumed that the constructs contributed equally to an individual's risk profile. The framework for the CRP model takes into the account the impact each factor had on the CRP, resulting in the various weightings. This proved to be one of the largest differences between the conceptual framework

and the final model produced from this study. Hanna et al.'s framework is shown again in Figure 5.2.

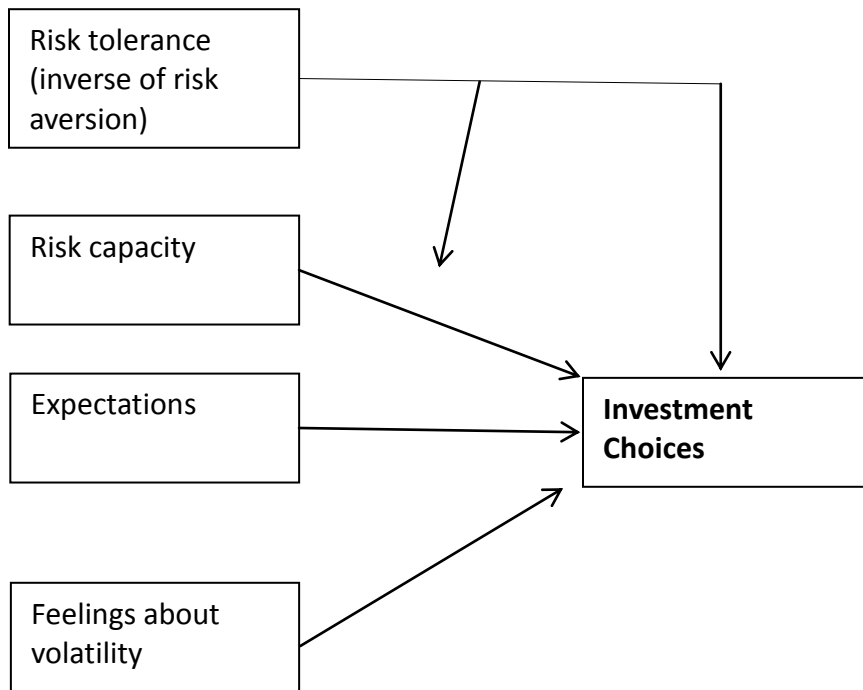


Figure 5.2 Hanna et al.'s (2008) Conceptual Model of Investment Choices Involving Risk

Implications

The results of this research showed that financial risk-assessment truly is a multidimensional process, and should be evaluated as such. Future studies should be conducted to test the composition of factors, but the PCA performed in this study clearly showed the presence of a number of factors contributing to an individual's risk profile. This goes a long way in supporting the notion that single-item, one-dimensional methods of risk-assessment are not an accurate way to evaluate an individual's risk profile today. Additionally, this study uncovered the relationships present among risk constructs, and reduced the constructs into similar factor groupings. This aspect of the study uncovered which aspects of the risk-assessment process have the most significant relationships. This clarity is something that academic researchers and financial practitioners can valuably use. For example, current versions of risk-assessment

procedures may not be as comprehensive as once thought. If the evaluation relies heavily on risk tolerance, the assessment would not be as multidimensional as the user thinks, nor would the instrument be as accurate as it needs to be. Risk tolerance, for example, accounted for less than 25% of an individual's overall CRP in this study. Relying solely on this construct to develop an accurate assessment would be a mistake.

Risk-profiling techniques that have developed a risk-profiling tool are abundant in the literature. However, these instruments typically equally-weight the variables that are included in the risk scale. As seen in this research, due to the impact that each variable had on an individual's CRP, weighting each variable evenly is not ideal. The tool in this study weighted each construct in accordance with the impact it had on the final model, as a result of the variable's explained variance in the factor analysis procedure. The CRP scale model provides a more accurate method of financial risk-assessment, as it weights each factor based on its impact on the overall model.

The effects of this study could be far-reaching, both in academia, as well as in the financial planning industry. Financial educators can use the results of this study to illustrate the comprehensive nature of the risk-assessment process. Financial institutions and practitioners could utilize this model as an accurate, comprehensive, yet simple method of risk-assessment for their clients. Additionally, the results from this study add to the existing body of literature in several ways. First, the eight-item instrument (which was reduced into three factors) extended upon previous risk-assessment research by offering a comprehensive, multidimensional foundation to the process. Specifically, it gives both practitioners and academic researchers a comprehensive financial risk-assessment tool that weights variables according to their impact on the overall model. Next, it gives financial institutions and practitioners a simple, yet

multidimensional tool to assess risk. Based on the literature reviewed in this study, an eight-item survey is neither too laborious for advisors to implement, nor is it too brief to fully encompass the complexity of an individual's risk profile.

The increase in regulatory oversight with respect to the financial services industry makes the results of this study significant as well. With the increase in regulations regarding the standards to which advisors know their clients, uphold suitability standards, and maintain fiduciary guidelines, it will become even more important for advisors to complete an accurate, comprehensive assessment of their clients' needs, objectives, and risk profiles (Brown, 2013). The use of intuitive, subjective judgments in assessing an individual's risk profile will not be acceptable. The broad, yet simple nature of this model would serve as an ideal method to assist in this process, specifically as it relates to risk-assessment. One of the overall implications of this study for financial advisors is clear: they should utilize a multidimensional tool (such as the CRP) to assess a client's risk comprehensively and accurately, yet quickly. Further, utilizing this CRP tool will allow academic researchers to implement a model that is not just efficient, but also valid, reliable, and theoretically based.

Policymakers should also appreciate a method of financial risk-assessment like the CRP. It is clear that the regulatory bodies that govern the financial services industry will continue to ensure that financial advisors are doing their very best to act in the best interest of their clients, and to know their clients. However, one-dimensional, simple models may do more harm than good in the financial planning process (Brown, 2013). The complete and accurate method of risk-assessment proposed in this study not only helps advisors, but it also protects the public by assessing individuals' risk accurately by using multidimensional constructs. Clients of advisors who used this method of assessment would know that an accurate evaluation of risk had been

done, which would help protect them from making poor financial planning decisions. Ultimately, this CRP assessment is a means by which policymakers can ensure financial practitioners are truly making their best efforts to know their clients and determine what is most suitable for them.

Implications for Goals-Based Planning

The advent of goals-based wealth management is another reason institutions and policymakers should note the findings from this study. One of the current limitations of the goals-based wealth management process is the lack of risk-assessment profiling. That is, the process involves tying individuals' goals directly into their financial planning needs. However, risk-assessment is often lost in this process. One of the reasons for this may be that prior risk-profiling instruments are too subjective in nature. Relating subjective risk constructs to an objective-based process, such as goals-based planning, may not make sense to practitioners or corporate financial planning policymakers. If a method of assessment existed that included objective factors, such as an individual's need to take risk in order to accomplish a goal, perhaps risk-profiling would be more prevalent in the goals-based planning model. The CRP model could be applied to a goals-based planning wealth management process. Because an individual's need to take financial risk explained over 50% of the overall model, it has a significant impact on one's overall risk profile. Additionally, an individual's perception of risk accounted for 30%. Both of these constructs naturally apply to the goals-based planning process. Goals-based wealth managers and institutions have a difficult task of applying a client's behavioral goals to a well-designed financial plan. Even the best of plans may end up failing, if the plan bares more risk than the client is comfortable taking along the way. Applying a risk-assessment process that incorporates the philosophies of goals-based management will make these plans more likely to succeed. Not only will the plan be well designed, but also clients will be more likely to stay the

course if their risk is assessed prior to plan implementation, and on an ongoing basis. The CRP model developed from this research can aid in this process. Further, with the onset of increased regulatory oversight in the financial services industry, risk-assessment procedures will be imperative for even goals-based wealth managers. The CRP method of assessment suffices this standard element of prudent financial planning and/or asset management.

Limitations

— It is important to remind the readers of this dissertation what this study is not. First, it is not meant to predict the risk-taking behavior of the participants in any way. Specifically, this research is not intended to predict an individual's actual asset allocation (or financial plan) based on the outcome of the CRP or CRP score. The CRP tool designed as a result of this study assigns an individual's risk profile to a target allocation model so that the profile can be linked to a measurable outcome. That is, the CRP assessment is designed to help practitioners and researchers quantify an individual's comprehensive financial risk profile. It is not meant to connect how an individual actually behaves with how they should behave, or act as a predictor of risk behavior in any way. Perhaps this is a topic for further research.

Additionally, the choice of the measurable outcome utilized in this study may not be ideal for those who do not have an investment portfolio (since an individual's CRP was tied to a measurable investment asset allocation framework). For the purposes of this study, the Delphi panel elected to utilize fairly simple asset allocation target models for a number of reasons. First, this type of connection (risk profile to a target allocation model) is common in practice. It is efficient to implement, and straightforward in nature. Second, logistically, it was practical for this study's sample. Had more detailed, personal questions been asked as a part of the risk-assessment questionnaire, fewer responses may have been gathered. That is, respondents may

have been put off by questions asking about their net worth, or actual asset allocation balances. In the Delphi group's opinion, the general, non-personal nature of the study allowed for more data to be obtained. Due to the nature of the profiling questions, target asset allocation models were chosen as the most appropriate measurable outcome for the CRP scale. Last, the Delphi panel struggled with forming a consensus on how to assign CRP scale scores to a measurable outcome variable, if a simple approach was not utilized. Therefore, the application of simple asset allocation models to the risk categories removed many of the concerns raised by the panel. For example, there were varying opinions on what constituted an asset class, and what should be included in each.

As noted throughout this research, the purpose of this study is exploratory in nature. Hopefully this research will be replicated in a variety of manners, including (but not limited to): the assignment of the risk profile to other measurable outcomes within an individual's financial plan, the sample size, and the geography of the sample demographic. Although the application of an asset allocation model was an ideal fit for this research, follow-up studies that utilize other forms of outcome variables would be interesting. For example, perhaps a more generalizable outcome would involve applying this risk framework to individuals' overall financial plan, and not just their investment portfolio. Prior studies that used this type of application are scarce in the literature. Because of this, asset allocation frameworks serve as the generally acceptable measure of connecting an individual's risk profile to a measurable outcome.

There are some additional factors to consider when reviewing this research, as well as some ideas to consider for replication studies. Further research should be conducted with a larger and more diverse population sample, to validate the model formed as a result of this study. Although the sample and sample size used in this study were acceptable for exploratory research,

it would be useful to test the results from a more generalizable demographic. In order for the CRP scale to become widely accepted across both the financial services industry and academia, follow-up studies that test the validity, reliability, and generalizability should be conducted. A nationwide sample that includes a more diverse dataset would be ideal.

As with any financial risk-profiling assessment, a number of factors could affect the participants' responses, such as an individual's mood at the time of sampling, the time of day, or the setting of where the survey is administered (Grable, 2000; Grable, Lytton, & O'Neil, 2004). Although these issues are prevalent in any risk-sampling procedure, they may have been a factor in the participants' responses during this study as well. While it may be ideal to control for these influences in future studies, it was not the premise of this research, and the majority of risk-profiling studies are done without controlling for these factors. Further, risk-assessments that are conducted by practitioners are subject to similar effects. Financial advisors do not have the opportunity to regularly control for outside influences, biases, and other factors. Therefore, controlling for these kinds of factors was not a significant concern in this study.

Summary

The results from this study were noteworthy in several respects. Overall, this research has extended previous attempts to define financial risk-assessment as a multidimensional process. Some of the outcomes were confirmatory in nature. For example, it was determined that individuals' willingness to take risk (tolerance) is not the only factor that contributes to their overall risk profile. That is, evaluating the risk tolerance construct by itself is not enough. This finding is relevant to academic researchers who have relied on risk tolerance estimates as the basis for their studies, as well as practitioners who must assess their clients' risk prior to determining the appropriate course of action with their financial plan. This result provided clear

evidence that financial risk-assessment goes beyond estimating risk tolerance, and that it is sincerely a multidimensional process. This supports other studies that have argued that financial risk-assessment is a multidimensional process (Grable & Lytton, 1999; Snelbecker et al., 1990). Additionally, this study determined what themes were instrumental in the comprehensive risk-assessment process—(1) risk need, (2) risk perception, and (3) future risk tolerance. These findings support the literature in that both subjective and objective measures are needed to accurately estimate an individual's financial risk profile (Adkins, 1997; Grable & Lytton, 1999; Hanna & Chen, 1997; Hanna et al., 2001; Kitces, 2006; Rajarajan, 2003).

One of the most profound outcomes of this research is that it explored how to take into consideration the impact that various risk constructs have on a CRP. The model for comprehensive risk-assessment in this study weighted an individual's multidimensional assessment of financial risk optimally, taking into consideration the impact that each construct had on the overall profile. Many of the risk-assessment frameworks developed in the literature do not take the weights of constructs into consideration when forming the outcome variable. Essentially, most financial risk-assessment models weight the items used in the survey equally. This would be sufficient if each variable had an equal impact on an individual's overall profile. However, the results from this study indicated otherwise. The risk variables had varying effects on an individual's CRP. Therefore, an equally-weighted estimate was not logical in establishing an overall risk-profiling score. Whether the CRP model from this study is utilized in the future or not, findings from this study suggest that future researchers need to be concerned with how input variables are weighted in the overall model. The CRP scale developed in this study may not be the final comprehensive risk-profiling tool. However, hopefully the results from this study provoke future researchers to consider the application of a model that is not equally-weighted in

assessing an individual's overall risk profile. Follow up studies should be conducted on this model to determine if the same relationships exist in the samples collected from other geographic areas, larger data sets, and other demographics in general. For example, will the risk variables be reduced into the same factors? Will the factors have similar contributions to an individual's CRP? Answers to these questions will provide needed insight with respect to the validity and reliability of the model created in this study. Thoughtful care, attention, and research should continue in the financial risk-assessment process to help solidify the purposes explored in this research. The future of accurate financial risk-assessment, fulfilled suitability and fiduciary guidelines, and successful financial planning may very well depend on it.

ⁱ *7-Factor Confirmatory Procedure*

The hypothesized empirical model for the study implied that there would be seven constructs that contributed to an individual's CRP. These constructs were assumed to be the direct function of the 14 items on the questionnaire. Specifically, it was suggested that both items in each construct would be grouped together as a part of the factor analysis procedure. For example, both risk composure items would be grouped together and retained, both risk capacity items would be reduced together and retained, etc. Since this was not the case as a result of the exploratory factor analysis, an additional procedure was run to see how the 14 items would have been grouped together in a seven-factor model. The purpose of this was to confirm if each item would get reduced into its hypothesized factor, if the model was constrained to seven factors. The results are shown in Table 5.1. This model was not utilized for a several reasons. First, this research was meant to be exploratory in nature. Therefore, an exploratory factor analysis was the ideal procedure to assess which risk constructs impact the CRP, and the impact that they have on the overall model. That is, this study was not meant to be confirmatory in nature. Therefore, analyses aimed at objectively, naturally isolating the optimal risk constructs were ideal for this process. The exploratory factor analysis accomplished this. Said differently, although an empirical model was proposed, there were no specific hypotheses regarding how many factors would truly emerge, what items or variables these factors would be comprised of, and what their impact (weight) on the CRP would be. Therefore, an exploratory factor analysis was the most appropriate. Additionally, the results of the seven-factor constrained model were less desirable than the exploratory model. The empirical model proposed seven different, but related factors. The constrained model did not generate these factors as predicted. For example, according to the original empirical model, both items in each construct should have been paired together in the factor analysis. However, this was oftentimes not the case. This result suggested that a more open approach (unconstrained) would be ideal to determine what relationships are present, and which factors are more impactful on the CRP.

Table 5.1 Factor Loadings for the Seven-Factor, Constrained Principal Components Solution

	Factor 1	Factor2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
Factor 1.							
RISKNEED1	0.85						
RISKNEED2	0.83						
RISKCAP2	0.51						
RISKPREF1	0.41						
Factor 2.							
RISKCAP1		0.82					
RISKTOL1		0.51					
RISKTOL2		0.44					
Factor 3.							
RISKPER1			0.88				
RISKPREF2			0.48				
Factor 4.							
RISKCOMP2				0.86			
RISKKNOWL2				0.51			
Factor 5.							
RISKCOMP1					-0.80		
Factor 6.							
RISKKNOWL1						0.96	
Factor 7.							
RISKPER2							0.96

Total Instrument $\alpha = 0.59$

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Appendix A - Comprehensive Risk Profile

Items

1. Which of the following statements comes closest to the amount of financial risk that you are willing to take when you save or make investments?
 - a. Not willing to take any financial risks
 - b. Take average financial risks expecting to earn average returns
 - c. Take above average financial risks expecting to earn above average returns
 - d. Take substantial financial risk expecting to earn substantial returns
2. How large of a decline in your investment's value would you be willing to accept in any one-year period? Assume for this example that your initial investment is worth \$100,000.
 - a. Less than \$5,000
 - b. \$10,000
 - c. \$20,000
 - d. \$25,000 or more
3. When you think of the word "risk," which of the following words comes to mind first?
 - a. Loss
 - b. Uncertainty
 - c. Opportunity
 - d. Thrill
4. Assume that your financial plan is statistically likely to fail. Which of the following actions would you perceive as the most appropriate way to increase the likelihood of your financial plan's success?
 - a. Lowering your future expectations
 - b. Saving more
 - c. Selling assets
 - d. Taking on more risk with your investments
5. Assume you had a portfolio with a balance of \$100,000. Given the best and worst case returns of the four investment choices below, which would you prefer over the course of a one-year period?
 - a. \$10,000 gain best case; \$0 loss worst case; \$4,500 gain average case

- b. \$18,000 gain best case; \$12,000 loss worst case; \$6,000 gain average case
 - c. \$26,000 gain best case; \$18,000 loss worst case; \$8,000 gain average case
 - d. \$35,000 gain best case; \$30,000 loss worst case; \$12,000 gain average case
6. Suppose a relative left you an inheritance of \$100,000, stipulating in the will that you had to invest all of the money into one of the following choices. Which one would you prefer?
- a. A savings account or money market mutual fund
 - b. A mutual fund that owns stocks and bonds
 - c. A portfolio of 15 common stocks
 - d. Commodities like gold, silver, and oil
7. Please answer the following by responding with a yes or no answer.
- a. Do you have a positive net worth (more assets than liabilities)?
 - b. Do you have an emergency fund equal to 4.5 months of living expenses (Could you live for 4.5 months simply on your savings)?
 - c. Do you have a savings ratio equal to 10% of your gross income?
 - d. Do you have an adequate amount of insurance?
8. Which of the following describes the length of time until you retire (or make significant withdrawals from your portfolio)?
- a. 0-5 years
 - b. 6-10 years
 - c. 11-20 years
 - d. 21+ years
9. When a quality asset you own lost value, how did you react? Examples of assets include: real estate, stocks, bonds, gold, etc.
- a. I sold the asset
 - b. I sold some of the asset, but not all of it
 - c. I made no changes
 - d. I bought more of the asset
10. How do outside influences such as friends, social groups, publications, or the media influence your financial decisions, such as investing in the stock market?
- a. They have a very significant impact on my financial decisions

- b. They have an average impact on my financial decisions
 - c. They have a little impact on my financial decisions
 - d. They have very little to no impact on my financial decisions
11. If interest rates rise, what will typically happen to bond prices?
- a. They will increase
 - b. They will decrease
 - c. They will stay the same
 - d. There is no relationship between interest rates and bond prices
12. True or False: Buying a single company's stock usually provides a safer return than a stock mutual fund.
- a. True
 - b. False
13. Given your current financial situation, which of the following describes your need to take risk with your finances, in order to accomplish your primary goal?
- a. I need to take extremely little to no financial risk to accomplish my goal
 - b. I need to take a little financial risk to accomplish my goal
 - c. I need to take a moderate amount of financial risk to accomplish my goal
 - d. I need to take considerable financial risk in order to accomplish my goal
14. Given your current financial situation, which of the following describes your need to take risk with your finances, in order to accomplish your secondary goal/ goals?
- a. I need to take extremely little to no financial risk to accomplish my goals
 - b. I need to take a little financial risk to accomplish my goals
 - c. I need to take a moderate amount of financial risk to accomplish my goals
 - d. I need to take considerable financial risk in order to accomplish my goals

Appendix B - CRP Scoring

1. $a = 1; b = 2; c = 3; d = 4$
2. $a = 1; b = 2; c = 3; d = 4$
3. $a = 1; b = 2; c = 3; d = 4$
4. $a = 1; b = 2; c = 3; d = 4$
5. $a = 1; b = 2; c = 3; d = 4$
6. $a = 1; b = 2; c = 3; d = 4$
7. $a = 1; b = 2; c = 3; d = 4$
8. $a = 1; b = 2; c = 3; d = 4$
9. $a = 1; b = 2; c = 3; d = 4$
10. $a = 1; b = 2; c = 3; d = 4$
11. $a = 1; b = 4$
12. $a = 1; b = 4$
13. $a = 1; b = 2; c = 3; d = 4$
14. $a = 1; b = 2; c = 3; d = 4$

Appendix C - Output and Syntax

```
DESCRIPTIVES VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2
RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2 AGE GENDER EDUCATION
/STATISTICS=MEAN STDDEV RANGE MIN MAX.
```

Descriptives

Notes

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Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2 AGE GENDER EDUCATION /STATISTICS=MEAN STDDEV RANGE MIN MAX.
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	Elapsed Time	00:00:00.017

Descriptive Statistics

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RISKPER1	321	3.00	1.00	4.00	1.9938	.57551
RISKPER2	321	3.00	1.00	4.00	1.7414	.79753
RISKPREF1	321	3.00	1.00	4.00	2.0685	.93289
RISKPREF2	321	3.00	1.00	4.00	2.2555	.86432
RISKCAP1	321	3.00	1.00	4.00	2.8816	.98028
RISKCAP2	321	3.00	1.00	4.00	2.1838	1.19655
RISKCOMP1	321	3.00	1.00	4.00	2.7383	.76652
RISKCOMP2	321	3.00	1.00	4.00	2.9159	.86373
RISKKNOWL1	321	3.00	1.00	4.00	2.8598	1.45848
RISKKNOWL2	321	3.00	1.00	4.00	3.8411	.67291
RISKNEED1	321	3.00	1.00	4.00	2.1713	.83212
RISKNEED2	321	3.00	1.00	4.00	2.1402	.78798
AGE	321	75.00	20.00	95.00	57.9003	14.84175
GENDER	321	1.00	1.00	2.00	1.5265	.50008
EDUCATION	321	3.00	1.00	4.00	2.2336	.76132
Valid N (listwise)	321					

CORRELATIONS

```

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCAP2 RISKCOMP1
RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2
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/MISSING=PAIRWISE.

```

Correlations

Notes

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Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics for each pair of variables are based on all the cases with valid data for that pair.
Syntax		CORRELATIONS /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2 /PRINT=TWOTAIL NOSIG /MISSING=PAIRWISE.
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		Correlations					
		RISKTOL1	RISKTOL2	RISKPER1	RISKPER2	RISKPREF1	RISKPREF2
RISKTOL1	Pearson Correlation	1	.510**	.152**	.271**	.419**	.239**
	Sig. (2-tailed)		.000	.006	.000	.000	.000
	N	321	321	321	321	321	321
RISKTOL2	Pearson Correlation	.510**	1	.022	.236**	.365**	.080
	Sig. (2-tailed)	.000		.700	.000	.000	.154
	N	321	321	321	321	321	321

RISKPER1	Pearson Correlation	.152**	.022	1	-.004	.094	.160**
	Sig. (2-tailed)	.006	.700		.950	.093	.004
	N	321	321	321	321	321	321
RISKPER2	Pearson Correlation	.271**	.236**	-.004	1	.234**	.132*
	Sig. (2-tailed)	.000	.000	.950		.000	.018
	N	321	321	321	321	321	321
RISKREF1	Pearson Correlation	.419**	.365**	.094	.234**	1	.230**
	Sig. (2-tailed)	.000	.000	.093	.000		.000
	N	321	321	321	321	321	321
RISKREF2	Pearson Correlation	.239**	.080	.160**	.132*	.230**	1
	Sig. (2-tailed)	.000	.154	.004	.018	.000	
	N	321	321	321	321	321	321
RISKCAP1	Pearson Correlation	.220**	.220**	-.068	.137*	.135*	.139*
	Sig. (2-tailed)	.000	.000	.226	.014	.015	.013
	N	321	321	321	321	321	321
RISKCAP2	Pearson Correlation	.190**	.075	.033	.017	-.014	-.082
	Sig. (2-tailed)	.001	.183	.551	.759	.801	.144
	N	321	321	321	321	321	321
RISKCOMP1	Pearson Correlation	.194**	.193**	.060	.104	.148**	.045
	Sig. (2-tailed)	.000	.001	.283	.064	.008	.426
	N	321	321	321	321	321	321
RISKCOMP2	Pearson Correlation	-.018	.062	.125*	.068	.104	.096
	Sig. (2-tailed)	.742	.271	.025	.223	.062	.086
	N	321	321	321	321	321	321
RISKKNOWL1	Pearson Correlation	.059	.196**	-.008	.060	.058	.024
	Sig. (2-tailed)	.295	.000	.880	.283	.303	.674
	N	321	321	321	321	321	321
RISKKNOWL2	Pearson Correlation	.016	.193**	-.148**	-.024	.182**	-.011
	Sig. (2-tailed)	.769	.001	.008	.663	.001	.850
	N	321	321	321	321	321	321
RISKNEED1	Pearson Correlation	.373**	.301**	.041	.180**	.327**	.143*
	Sig. (2-tailed)	.000	.000	.460	.001	.000	.010
	N	321	321	321	321	321	321
RISKNEED2	Pearson Correlation	.376**	.330**	.133*	.127*	.276**	.071
	Sig. (2-tailed)	.000	.000	.017	.022	.000	.204
	N	321	321	321	321	321	321

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RISKCAP1	RISKCAP2	RISKCOMP1	RISKCOMP2	RISKKNOWL1
RISKTOL1	Pearson Correlation	.220**	.190**	.194**	-.018	.059
	Sig. (2-tailed)	.000	.001	.000	.742	.295
	N	321	321	321	321	321
RISKTOL2	Pearson Correlation	.220**	.075	.193**	.062	.196**
	Sig. (2-tailed)	.000	.183	.001	.271	.000
	N	321	321	321	321	321
RISKPER1	Pearson Correlation	-.068	.033	.060	.125*	-.008
	Sig. (2-tailed)	.226	.551	.283	.025	.880
	N	321	321	321	321	321
RISKPER2	Pearson Correlation	.137*	.017	.104	.068	.060
	Sig. (2-tailed)	.014	.759	.064	.223	.283
	N	321	321	321	321	321
RISKREF1	Pearson Correlation	.135*	-.014	.148**	.104	.058
	Sig. (2-tailed)	.015	.801	.008	.062	.303
	N	321	321	321	321	321
RISKREF2	Pearson Correlation	.139*	-.082	.045	.096	.024
	Sig. (2-tailed)	.013	.144	.426	.086	.674
	N	321	321	321	321	321
RISKCAP1	Pearson Correlation	1	-.232**	.100	.044	.168**
	Sig. (2-tailed)		.000	.073	.437	.003
	N	321	321	321	321	321
RISKCAP2	Pearson Correlation	-.232**	1	.093	-.009	-.132*
	Sig. (2-tailed)	.000		.094	.870	.018
	N	321	321	321	321	321
RISKCOMP1	Pearson Correlation	.100	.093	1	.151**	.118*
	Sig. (2-tailed)	.073	.094		.007	.035
	N	321	321	321	321	321
RISKCOMP2	Pearson Correlation	.044	-.009	.151**	1	-.047
	Sig. (2-tailed)	.437	.870	.007		.405
	N	321	321	321	321	321
RISKKNOWL1	Pearson Correlation	.168**	-.132*	.118*	-.047	1
	Sig. (2-tailed)	.003	.018	.035	.405	
	N	321	321	321	321	321
RISKKNOWL2	Pearson Correlation	.085	-.010	.010	.090	.187**
	Sig. (2-tailed)	.128	.856	.858	.108	.001

		321	321	321	321	321
N		321	321	321	321	321
RISKNEED1	Pearson Correlation	-.128*	.351**	.017	.007	-.008
	Sig. (2-tailed)	.021	.000	.767	.900	.880
N		321	321	321	321	321
RISKNEED2	Pearson Correlation	-.071	.291**	.014	-.070	-.032
	Sig. (2-tailed)	.201	.000	.798	.212	.570
N		321	321	321	321	321

** . Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Correlations

		RISKKNOWL2	RISKNEED1	RISKNEED2
RISKTOL1	Pearson Correlation	.016	.373**	.376**
	Sig. (2-tailed)	.769	.000	.000
	N	321	321	321
RISKTOL2	Pearson Correlation	.193**	.301**	.330**
	Sig. (2-tailed)	.001	.000	.000
	N	321	321	321
RISKPER1	Pearson Correlation	-.148**	.041	.133*
	Sig. (2-tailed)	.008	.460	.017
	N	321	321	321
RISKPER2	Pearson Correlation	-.024	.180**	.127*
	Sig. (2-tailed)	.663	.001	.022
	N	321	321	321
RISKPREF1	Pearson Correlation	.182**	.327**	.276**
	Sig. (2-tailed)	.001	.000	.000
	N	321	321	321
RISKPREF2	Pearson Correlation	-.011	.143*	.071
	Sig. (2-tailed)	.850	.010	.204
	N	321	321	321
RISKCAP1	Pearson Correlation	.085	-.128*	-.071
	Sig. (2-tailed)	.128	.021	.201
	N	321	321	321
RISKCAP2	Pearson Correlation	-.010	.351**	.291**
	Sig. (2-tailed)	.856	.000	.000
	N	321	321	321
RISKCOMP1	Pearson Correlation	.010	.017	.014

	Sig. (2-tailed)	.858	.767	.798
	N	321	321	321
RISKCOMP2	Pearson Correlation	.090	.007	-.070
	Sig. (2-tailed)	.108	.900	.212
	N	321	321	321
RISKKNOWL1	Pearson Correlation	.187**	-.008	-.032
	Sig. (2-tailed)	.001	.880	.570
	N	321	321	321
RISKKNOWL2	Pearson Correlation	1	.099	.077
	Sig. (2-tailed)		.077	.166
	N	321	321	321
RISKNEED1	Pearson Correlation	.099	1	.669**
	Sig. (2-tailed)	.077		.000
	N	321	321	321
RISKNEED2	Pearson Correlation	.077	.669**	1
	Sig. (2-tailed)	.166	.000	
	N	321	321	321

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

FACTOR

```

/VARIABLES RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1
RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2
/MISSING LISTWISE
/ANALYSIS RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2
RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2
/PRINT INITIAL KMO EXTRACTION ROTATION FSCORE
/FORMAT SORT
/PLOT EIGEN
/CRITERIA MINEIGEN(1) ITERATE(50)
/EXTRACTION PC
/CRITERIA ITERATE(50) DELTA(0)
/ROTATION OBLIMIN
/METHOD=CORRELATION.

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Factor Analysis

Notes

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Missing Value Handling	Definition of Missing	MISSING=EXCLUDE: User-defined missing values are treated as missing.
	Cases Used	LISTWISE: Statistics are based on cases with no missing values for any variable used.
Syntax		<pre> FACTOR /VARIABLES RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2 /MISSING LISTWISE /ANALYSIS RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2 /PRINT INITIAL KMO EXTRACTION ROTATION FSCORE /FORMAT SORT /PLOT EIGEN /CRITERIA MINEIGEN(1) ITERATE(50) /EXTRACTION PC /CRITERIA ITERATE(50) DELTA(0) /ROTATION OBLIMIN /METHOD=CORRELATION. </pre>

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KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.704
Bartlett's Test of Sphericity	Approx. Chi-Square	773.136
	df	91
	Sig.	.000

Communalities

	Initial	Extraction
RISKTOL1	1.000	.663
RISKTOL2	1.000	.592
RISKPER1	1.000	.461
RISKPER2	1.000	.311
RISKREF1	1.000	.522
RISKREF2	1.000	.567
RISKCAP1	1.000	.542
RISKCAP2	1.000	.624
RISKCOMP1	1.000	.710
RISKCOMP2	1.000	.720
RISKKNOWL1	1.000	.356
RISKKNOWL2	1.000	.767
RISKNEED1	1.000	.736
RISKNEED2	1.000	.694

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	2.989	21.349	21.349	2.989	21.349
2	1.778	12.701	34.051	1.778	12.701
3	1.329	9.491	43.542	1.329	9.491
4	1.122	8.011	51.553	1.122	8.011
5	1.047	7.482	59.035	1.047	7.482
6	.970	6.932	65.967		
7	.821	5.866	71.833		
8	.782	5.584	77.417		
9	.715	5.106	82.523		
10	.638	4.561	87.084		
11	.585	4.177	91.261		
12	.537	3.833	95.094		
13	.392	2.800	97.894		
14	.295	2.106	100.000		

Extraction Method: Principal Component Analysis.

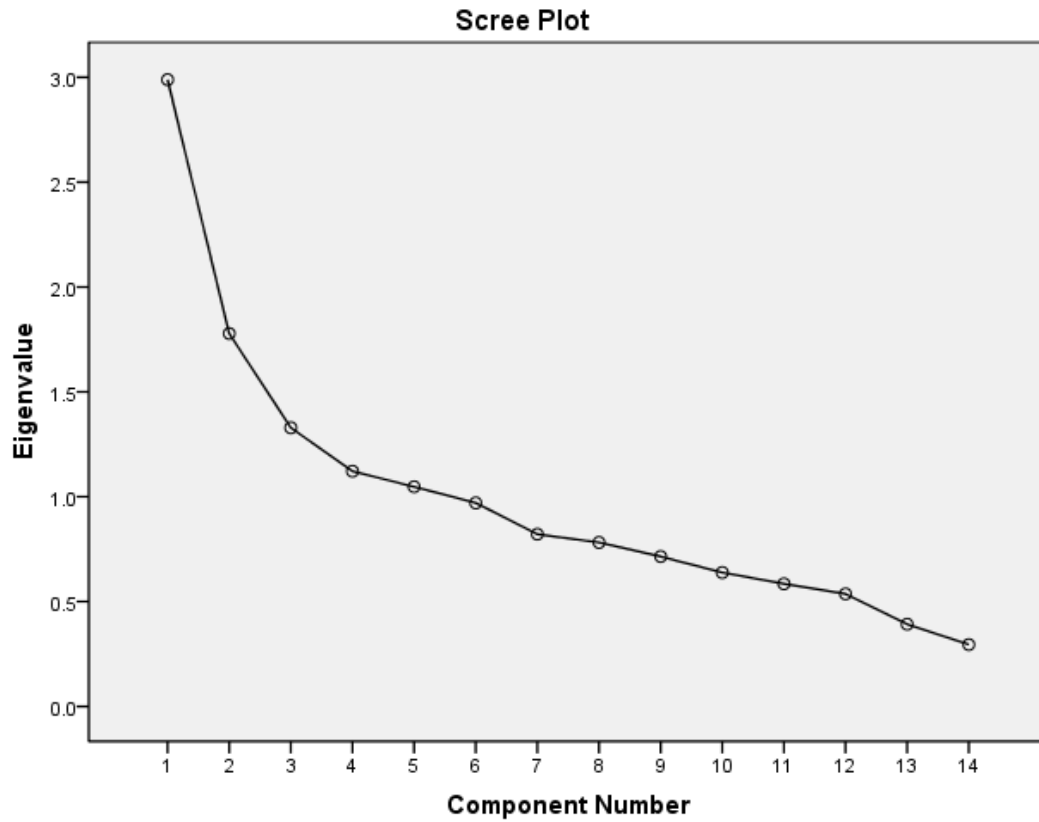
Total Variance Explained

Component	Extraction Sums of Squared Loadings ^a	Rotation Sums of Squared Loadings ^a
	Cumulative %	Total
1	21.349	2.885
2	34.051	1.707
3	43.542	1.325
4	51.553	1.251
5	59.035	1.404
6		
7		
8		
9		
10		
11		

12		
13		
14		

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.



Component Matrix^a

	Component				
	1	2	3	4	5
RISKTOL1	.761	.073	.104	-.165	-.204
RISKNEED1	.696	-.455	-.131	-.031	.162
RISKTOL2	.690	.228	-.206	.044	-.139
RISKNEED2	.673	-.452	-.127	-.104	.101
RISKPREF1	.648	.196	.054	-.012	.245

RISKPER2	.424	.195	.119	-.161	-.231
RISKCAP1	.184	.666	-.037	-.221	-.122
RISKCAP2	.289	-.612	-.065	.296	-.273
RISKKNOWL1	.140	.451	-.350	.050	-.089
RISKPER1	.178	-.092	.637	.067	.103
RISKKNOWL2	.199	.225	-.568	.347	.484
RISKPREF2	.323	.226	.459	-.253	.370
RISKCOMP2	.098	.201	.363	.667	.306
RISKCOMP1	.274	.248	.162	.530	-.515

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Pattern Matrix^a

	Component				
	1	2	3	4	5
RISKNEED1	.835	-.291	-.077	.004	.139
RISKNEED2	.819	-.259	-.019	-.075	.135
RISKTOL1	.667	.212	.166	-.062	-.251
RISKPREF1	.562	.279	-.145	.247	.009
RISKTOL2	.559	.183	-.223	-.047	-.323
RISKPER2	.311	.276	.175	-.085	-.241
RISKCAP2	.367	-.688	.092	-.036	-.264
RISKCAP1	-.010	.667	-.080	-.114	-.193
RISKPREF2	.268	.482	.227	.342	.270
RISKKNOWL2	.182	.002	-.855	.219	.125
RISKKNOWL1	.009	.294	-.387	-.125	-.227
RISKCOMP2	-.132	-.075	-.167	.831	-.232
RISKPER1	.103	.023	.444	.451	-.012
RISKCOMP1	-.044	-.096	.047	.236	-.836

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 38 iterations.

Structure Matrix

	Component				
	1	2	3	4	5
RISKNEED1	.788	-.239	-.016	.064	.055
RISKNEED2	.770	-.215	.032	-.009	.050
RISKTOL1	.723	.294	.160	.015	-.371
RISKTOL2	.607	.286	-.237	-.021	-.451
RISKPREF1	.600	.344	-.111	.299	-.116
RISKPER2	.369	.325	.149	-.036	-.318
RISKCAP1	.060	.693	-.138	-.097	-.303
RISKCAP2	.349	-.624	.117	-.040	-.208
RISKPREF2	.309	.470	.268	.424	.190
RISKKNOWL2	.148	.051	-.818	.162	.042
RISKKNOWL1	.038	.341	-.429	-.155	-.307
RISKCOMP2	-.035	.000	-.110	.790	-.179
RISKPER1	.167	.035	.488	.502	.023
RISKCOMP1	.094	.036	.008	.196	-.802

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Correlation Matrix

Component	1	2	3	4	5
1	1.000	.083	.043	.092	-.146
2	.083	1.000	-.048	.051	-.151
3	.043	-.048	1.000	.093	.076
4	.092	.051	.093	1.000	.043
5	-.146	-.151	.076	.043	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Score Coefficient Matrix

	Component				
	1	2	3	4	5
RISKTOL1	.241	.147	.155	-.084	-.182
RISKTOL2	.186	.111	-.149	-.086	-.245
RISKPER1	.050	.023	.354	.382	.048
RISKPER2	.115	.180	.152	-.101	-.188
RISKPREF1	.202	.173	-.078	.196	.059
RISKPREF2	.122	.308	.209	.309	.277
RISKCAP1	.001	.406	-.041	-.131	-.158
RISKCAP2	.112	-.416	.055	-.046	-.216
RISKCOMP1	-.048	-.077	.030	.106	-.655
RISKCOMP2	-.066	-.075	-.121	.666	-.102
RISKKNOWL1	-.012	.165	-.290	-.143	-.195
RISKKNOWL2	.041	-.028	-.646	.180	.127
RISKNEED1	.297	-.163	-.041	.020	.138
RISKNEED2	.294	-.140	.003	-.046	.126

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Score Covariance Matrix

Component	1	2	3	4	5
1	1.069	.130	2.050	.223	.011
2	.130	.880	.230	.046	1.840
3	2.050	.230	3.062	.274	1.201
4	.223	.046	.274	1.051	-.162
5	.011	1.840	1.201	-.162	4.010

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

RELIABILITY

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCAP2 RISKCOMP1
RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2

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/MODEL=ALPHA

/SUMMARY=TOTAL.

Reliability

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	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
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[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: UNCONSTRAINED 14-ITEM

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.590	14

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RISKTOL1	31.8380	21.455	.556	.537
RISKTOL2	31.9470	20.357	.514	.524
RISKPER1	32.0000	23.700	.098	.591
RISKPER2	32.2523	21.908	.273	.565
RISKPREF1	31.9252	20.038	.440	.530
RISKPREF2	31.7383	22.169	.205	.577
RISKCAP1	31.1121	22.475	.123	.594
RISKCAP2	31.8100	22.504	.057	.617
RISKCOMP1	31.2555	22.316	.232	.572
RISKCOMP2	31.0779	23.085	.090	.597
RISKKNOWL1	31.1340	21.135	.098	.623
RISKKNOWL2	30.1526	23.067	.164	.583
RISKNEED1	31.8224	20.678	.424	.537
RISKNEED2	31.8536	21.200	.380	.547

RELIABILITY

```

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCAP2 RISKCOMP1
RISKCOMP2 RISKKNOWL2 RISKNEED1 RISKNEED2
/SCALE('UNCONSTRAINED 13-ITEM') ALL
/MODEL=ALPHA
/SUMMARY=TOTAL.

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Reliability

Notes

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Notes

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Syntax		RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL2 RISKNEED1 RISKNEED2 /SCALE('UNCONSTRAINED 13-ITEM') ALL /MODEL=ALPHA /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.000
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Scale: UNCONSTRAINED 13-ITEM

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
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Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RISKTOL1	28.9782	18.103	.585	.568
RISKTOL2	29.0872	17.355	.489	.564
RISKPER1	29.1402	20.240	.109	.624
RISKPER2	29.3925	18.602	.276	.601
RISKPREF1	29.0654	16.749	.460	.562
RISKPREF2	28.8785	18.782	.214	.612
RISKCAP1	28.2523	19.508	.077	.642
RISKCAP2	28.9502	18.598	.107	.648
RISKCOMP1	28.3956	19.134	.211	.612
RISKCOMP2	28.2181	19.521	.114	.630
RISKKNOWL2	27.2928	19.989	.115	.625
RISKNEED1	28.9626	17.211	.468	.565
RISKNEED2	28.9938	17.681	.428	.575

RELIABILITY

```

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCOMP1 RISKCOMP2
RISKKNOWL2 RISKNEED1 RISKNEED2
/SCALE('UNCONSTRAINED 12-ITEM') ALL
/MODEL=ALPHA
/SUMMARY=TOTAL.

```

Reliability

Notes

Output Created		12-Mar-2014 14:34:11
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCAP1 RISKCOMP1 RISKCOMP2 RISKKNOWL2 RISKNEED1 RISKNEED2 /SCALE('UNCONSTRAINED 12-ITEM') ALL /MODEL=ALPHA /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.000
	Elapsed Time	00:00:00.000

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: UNCONSTRAINED 12-ITEM

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.648	12

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RISKTOL1	26.7944	15.814	.569	.596
RISKTOL2	26.9034	14.956	.503	.589
RISKPER1	26.9564	17.748	.107	.652
RISKPER2	27.2087	16.097	.291	.627
RISKPREF1	26.8816	14.180	.505	.582
RISKPREF2	26.6947	16.075	.256	.634
RISKCAP1	26.0685	16.427	.152	.659
RISKCOMP1	26.2118	16.767	.198	.643
RISKCOMP2	26.0343	16.964	.125	.659
RISKKNOWL2	25.1090	17.435	.126	.652
RISKNEED1	26.7788	15.373	.388	.609
RISKNEED2	26.8100	15.692	.366	.614

RELIABILITY

```

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCOMP1 RISKKNOWL2
RISKNEED1 RISKNEED2
/SCALE('UNCONSTRAINED 11-ITEM') ALL
/MODEL=ALPHA
/SUMMARY=TOTAL.

```

Reliability

Notes

Output Created		12-Mar-2014 14:34:34
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCOMP1 RISKKNOWL2 RISKNEED1 RISKNEED2 /SCALE('UNCONSTRAINED 11-ITEM') ALL /MODEL=ALPHA /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.000
	Elapsed Time	00:00:00.000

Scale: UNCONSTRAINED 11-ITEM

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.659	11

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RISKTOL1	23.8785	14.163	.606	.601
RISKTOL2	23.9875	13.406	.517	.597
RISKPER1	24.0405	16.239	.085	.668
RISKPER2	24.2928	14.558	.291	.640
RISKPREF1	23.9657	12.714	.508	.592
RISKPREF2	23.7788	14.585	.247	.649
RISKCAP1	23.1526	14.867	.150	.674
RISKCOMP1	23.2960	15.334	.174	.660
RISKKNOWL2	22.1931	15.906	.113	.667
RISKNEED1	23.8629	13.750	.409	.617
RISKNEED2	23.8941	13.964	.404	.619

RELIABILITY

```

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCOMP1 RISKKNOWL2 RISKNEED1
RISKNEED2
/SCALE('UNCONSTRAINED 10-ITEM') ALL
/MODEL=ALPHA
/SUMMARY=TOTAL.

```

Reliability

Notes

Output Created		12-Mar-2014 14:34:59
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCOMP1 RISKKNOWL2 RISKNEED1 RISKNEED2 /SCALE('UNCONSTRAINED 10-ITEM') ALL /MODEL=ALPHA /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.000

Notes

Output Created		12-Mar-2014 14:34:59
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		<pre> RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCOMP1 RISKKNOWL2 RISKNEED1 RISKNEED2 /SCALE('UNCONSTRAINED 10-ITEM') ALL /MODEL=ALPHA /SUMMARY=TOTAL. </pre>
Resources	Processor Time	00:00:00.000
	Elapsed Time	00:00:00.014

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: UNCONSTRAINED 10-ITEM

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.674	10

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RISKTOL1	20.9969	12.303	.588	.618
RISKTOL2	21.1059	11.645	.492	.619
RISKPER1	21.1589	14.065	.109	.684
RISKPER2	21.4112	12.674	.274	.663
RISKPREF1	21.0841	10.865	.509	.610
RISKPREF2	20.8972	12.724	.226	.674
RISKCOMP1	20.4143	13.387	.159	.683
RISKKNOWL2	19.3115	13.921	.098	.689
RISKNEED1	20.9813	11.443	.485	.618
RISKNEED2	21.0125	11.756	.461	.625

RELIABILITY

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCOMP1 RISKNEED1 RISKNEED2

/SCALE('UNCONSTRAINED 9-ITEM') ALL

/MODEL=ALPHA

/SUMMARY=TOTAL.

Reliability

Notes

Output Created		12-Mar-2014 14:35:14
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKCOMP1 RISKNEED1 RISKNEED2 /SCALE('UNCONSTRAINED 9-ITEM') ALL /MODEL=ALPHA /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.000
	Elapsed Time	00:00:00.000

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: UNCONSTRAINED 9-ITEM

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.689	9

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RISKTOL1	17.1558	11.369	.609	.631
RISKTOL2	17.2648	10.902	.469	.641
RISKPER1	17.3178	13.005	.141	.698
RISKPER2	17.5701	11.702	.290	.678
RISKREF1	17.2430	10.147	.489	.633
RISKREF2	17.0561	11.766	.238	.692
RISKCOMP1	16.5732	12.452	.163	.702
RISKNEED1	17.1402	10.608	.483	.636
RISKNEED2	17.1713	10.892	.463	.642

RELIABILITY

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKNEED1 RISKNEED2

/SCALE('UNCONSTRAINED 8-ITEM') ALL

/MODEL=ALPHA

/SUMMARY=TOTAL.

Reliability

Notes

Output Created		12-Mar-2014 14:35:33
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKNEED1 RISKNEED2 /SCALE('UNCONSTRAINED 8-ITEM') ALL /MODEL=ALPHA /SUMMARY=TOTAL.
Resources	Processor Time	00:00:00.016
	Elapsed Time	00:00:00.015

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: UNCONSTRAINED 8-ITEM

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.702	8

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
RISKTOL1	14.4174	10.063	.600	.644
RISKTOL2	14.5265	9.663	.450	.660
RISKPER1	14.5794	11.588	.136	.716
RISKPER2	14.8318	10.359	.284	.697
RISKPREF1	14.5047	8.888	.484	.650
RISKPREF2	14.3178	10.355	.243	.709
RISKNEED1	14.4019	9.160	.516	.643
RISKNEED2	14.4330	9.440	.494	.649

FACTOR

```

/VARIABLES RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKNEED1 RISKNEED2
/MISSING LISTWISE
/ANALYSIS RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKNEED1 RISKNEED2
/PRINT INITIAL KMO EXTRACTION ROTATION FSCORE
/FORMAT SORT
/PLOT EIGEN
/CRITERIA MINEIGEN(1) ITERATE(50)
/EXTRACTION PC
/CRITERIA ITERATE(50) DELTA(0)
/ROTATION OBLIMIN
/METHOD=CORRELATION.

```

Factor Analysis

Notes

Output Created		12-Mar-2014 14:36:10
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
Missing Value Handling	Definition of Missing	MISSING=EXCLUDE: User-defined missing values are treated as missing.
	Cases Used	LISTWISE: Statistics are based on cases with no missing values for any variable used.
Syntax		<pre> FACTOR /VARIABLES RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKNEED1 RISKNEED2 /MISSING LISTWISE /ANALYSIS RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKNEED1 RISKNEED2 /PRINT INITIAL KMO EXTRACTION ROTATION FSCORE /FORMAT SORT /PLOT EIGEN /CRITERIA MINEIGEN(1) ITERATE(50) /EXTRACTION PC /CRITERIA ITERATE(50) DELTA(0) /ROTATION OBLIMIN /METHOD=CORRELATION. </pre>
Resources	Processor Time	00:00:00.187
	Elapsed Time	00:00:00.250
	Maximum Memory Required	9264 (9.047K) bytes

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.733
Bartlett's Test of Sphericity	Approx. Chi-Square	520.948
	df	28
	Sig.	.000

Communalities

	Initial	Extraction
RISKTOL1	1.000	.606
RISKTOL2	1.000	.538
RISKPER1	1.000	.713
RISKPER2	1.000	.521
RISKPREF1	1.000	.492
RISKPREF2	1.000	.576
RISKNEED1	1.000	.740
RISKNEED2	1.000	.812

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	2.813	35.165	35.165	2.813	35.165
2	1.130	14.121	49.286	1.130	14.121
3	1.056	13.200	62.486	1.056	13.200
dimen 4	.830	10.377	72.863		
sion0 5	.777	9.714	82.578		
6	.628	7.844	90.422		
7	.453	5.661	96.083		
8	.313	3.917	100.000		

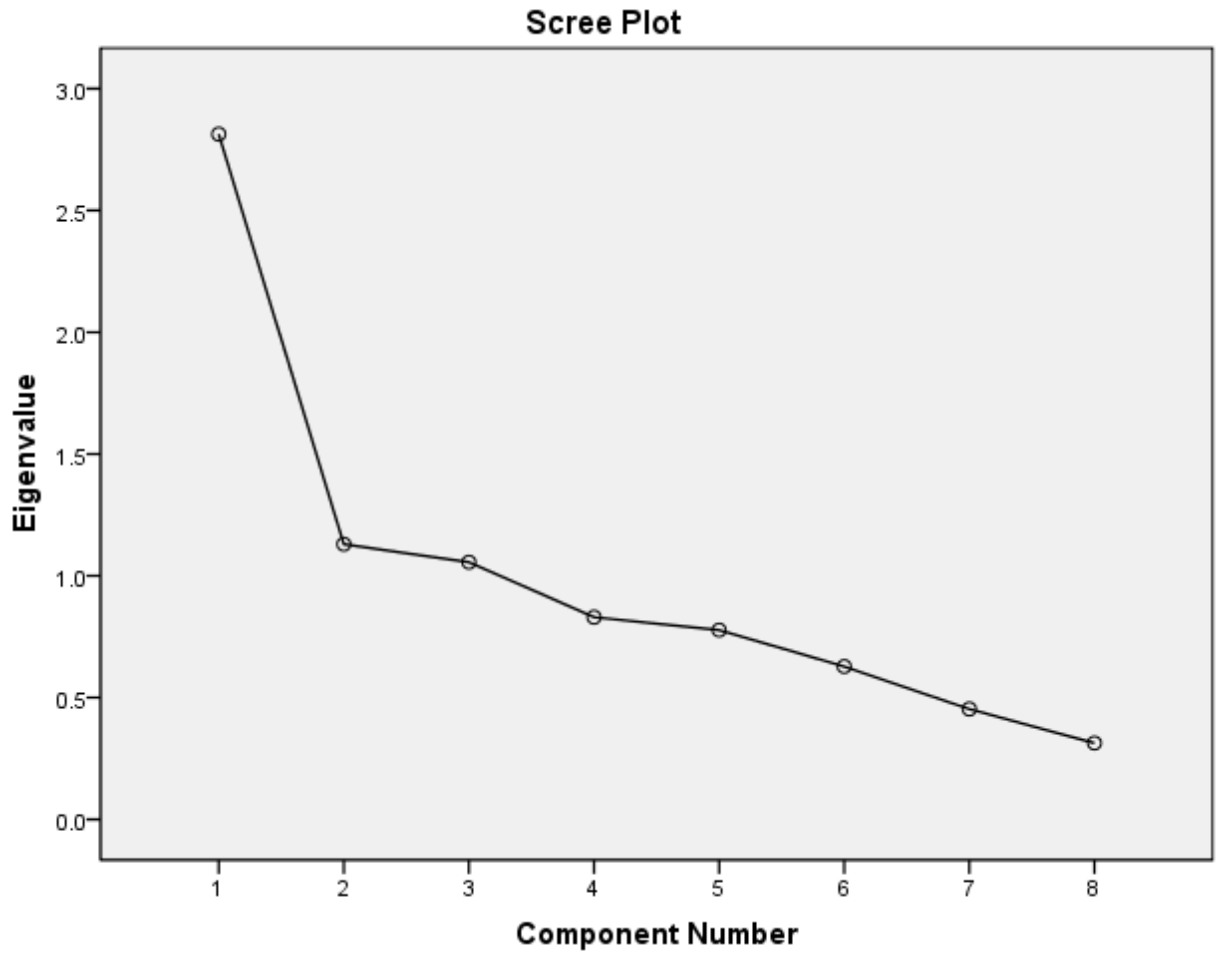
Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Extraction Sums of Squared Loadings	Rotation Sums of Squared Loadings ^a
	Cumulative %	Total
1	35.165	2.148
2	49.286	1.330
3	62.486	2.121
4		
5		
6		
7		
8		

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.



Component Matrix^a

	Component		
	1	2	3
RISKTOL1	.760	.119	-.118
RISKNEED1	.719	-.364	.299
RISKNEED2	.703	-.384	.413
RISKTOL2	.667	-.117	-.282
RISKPREF1	.657	.171	-.177
RISKPREF2	.347	.675	.029
RISKPER1	.203	.565	.594
RISKPER2	.431	.135	-.563

Extraction Method: Principal Component Analysis.

Component Matrix^a

	Component		
	1	2	3
RISKTOL1	.760	.119	-.118
RISKNEED1	.719	-.364	.299
RISKNEED2	.703	-.384	.413
RISKTOL2	.667	-.117	-.282
RISKREF1	.657	.171	-.177
RISKREF2	.347	.675	.029
RISKPER1	.203	.565	.594
RISKPER2	.431	.135	-.563

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Pattern Matrix^a

	Component		
	1	2	3
RISKNEED2	.902	.014	.011
RISKNEED1	.832	-.023	-.098
RISKPER1	.134	.824	.254
RISKREF2	-.184	.663	-.325
RISKPER2	-.160	-.083	-.753
RISKTOL2	.304	-.113	-.604
RISKTOL1	.314	.191	-.573
RISKREF1	.185	.186	-.572

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 13 iterations.

Structure Matrix

	Component		
	1	2	3
RISKNEED2	.901	.132	-.230
RISKNEED1	.855	.101	-.315
RISKPER1	.177	.806	.100
RISKREF2	-.010	.685	-.372

RISKPER2	.029	.004	-.699
RISKTOL1	.491	.315	-.683
RISKTOL2	.448	.013	-.668
RISKPREF1	.362	.292	-.648

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Correlation Matrix

Component	1	2	3
1	1.000	.133	-.265
2	.133	1.000	-.143
3	-.265	-.143	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Score Coefficient Matrix

	Component		
	1	2	3
RISKTOL1	.116	.131	-.296
RISKTOL2	.113	-.123	-.327
RISKPER1	.088	.692	.195
RISKPER2	-.169	-.095	-.462
RISKPREF1	.043	.129	-.309
RISKPREF2	-.152	.541	-.185
RISKNEED1	.466	-.038	.029
RISKNEED2	.517	-.005	.101

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Notes

Output Created	12-Mar-2014 14:56:37
Comments	
Input	Data
	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav

	Active Dataset	DataSet1	
	Filter	<none>	
	Weight	<none>	
	Split File	<none>	
	N of Rows in Working Data File		321
Missing Value Handling	Definition of Missing	MISSING=EXCLUDE: User-defined missing values are treated as missing.	
	Cases Used	LISTWISE: Statistics are based on cases with no missing values for any variable used.	
Syntax		<pre> FACTOR /VARIABLES RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKNEED1 RISKNEED2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 /MISSING LISTWISE /ANALYSIS RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKNEED1 RISKNEED2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 /PRINT INITIAL KMO EXTRACTION ROTATION FSCORE /FORMAT SORT /PLOT EIGEN /CRITERIA MINEIGEN(1) ITERATE(50) /EXTRACTION PC /CRITERIA ITERATE(50) DELTA(0) /ROTATION OBLIMIN /METHOD=CORRELATION. </pre>	
Resources	Processor Time		00:00:00.203
	Elapsed Time		00:00:00.187
	Maximum Memory Required		25128 (24.539K) bytes

Notes

Output Created	12-Mar-2014 15:33:45
Comments	

Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=RISKNEED RISKPERCEPTION RISKTOLERANCE /SCALE('3-FACTOR, 8-ITEM MODEL') ALL /MODEL=ALPHA /STATISTICS=SCALE.
Resources	Processor Time	00:00:00.000
	Elapsed Time	00:00:00.000

RELIABILITY

```

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKNEED1 RISKNEED2
/SCALE('8-ITEM MODEL') ALL
/MODEL=ALPHA
/STATISTICS=SCALE.

```

Reliability

Notes

Output Created		12-Mar-2014 15:36:12
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav

	Active Dataset	DataSet1	
	Filter	<none>	
	Weight	<none>	
	Split File	<none>	
	N of Rows in Working Data File		321
	Matrix Input		
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.	
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.	
Syntax		RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKPREF1 RISKPREF2 RISKNEED1 RISKNEED2 /SCALE('8-ITEM MODEL') ALL /MODEL=ALPHA /STATISTICS=SCALE.	
Resources	Processor Time		00:00:00.000
	Elapsed Time		00:00:00.000

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: 8-ITEM MODEL

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.702	8

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16.5732	12.452	3.52869	8

RELIABILITY

```

/VARIABLES=RISKNEED1 RISKNEED2
/SCALE('RISK NEED') ALL
/MODEL=ALPHA
/STATISTICS=SCALE.
    
```

Reliability

Notes

Output Created		12-Mar-2014 15:36:42
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.

Syntax	RELIABILITY		
	/VARIABLES=RISKNEED1 RISKNEED2		
	/SCALE('RISK NEED') ALL		
	/MODEL=ALPHA		
	/STATISTICS=SCALE.		
Resources	Processor Time		00:00:00.000
	Elapsed Time		00:00:00.000

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: RISK NEED

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.801	2

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
4.3115	2.190	1.47991	2

RELIABILITY
 /VARIABLES=RISKPER1 RISKREF2
 /SCALE('RISK PERCEPTION') ALL
 /MODEL=ALPHA
 /STATISTICS=SCALE.

Reliability

Notes

Output Created		12-Mar-2014 15:37:12
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=RISKPER1 RISKREF2 /SCALE('RISK PERCEPTION') ALL /MODEL=ALPHA /STATISTICS=SCALE.
Resources	Processor Time	00:00:00.000
	Elapsed Time	00:00:00.000

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: RISK PERCEPTION

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.258	2

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
4.2492	1.238	1.11252	2

RELIABILITY

```

/VARIABLES=RISKTOL1 RISKTOL2 RISKPREF1 RISKPER2
/SCALE('RISK TOLERANCE') ALL
/MODEL=ALPHA
/STATISTICS=SCALE.
    
```

Reliability

Notes

Output Created	12-Mar-2014 15:37:43
Comments	

Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure.
Syntax		RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPREF1 RISKPER2 /SCALE('RISK TOLERANCE') ALL /MODEL=ALPHA /STATISTICS=SCALE.
Resources	Processor Time	00:00:00.000
	Elapsed Time	00:00:00.000

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Scale: RISK TOLERANCE

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.647	4

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
8.0125	4.687	2.16503	4

FACTOR

```

/VARIABLES RISKNEED RISKPERCEPTION RISKTOLERANCE
/MISSING LISTWISE
/ANALYSIS RISKNEED RISKPERCEPTION RISKTOLERANCE
/PRINT INITIAL KMO EXTRACTION ROTATION FSCORE
/FORMAT SORT
/PLOT EIGEN
/CRITERIA FACTORS(3) ITERATE(50)
/EXTRACTION PC
/CRITERIA ITERATE(50) DELTA(0)
/ROTATION OBLIMIN
/METHOD=CORRELATION.
    
```

Factor Analysis

Notes

Output Created		12-Mar-2014 15:38:33
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>

	N of Rows in Working Data File	321
Missing Value Handling	Definition of Missing	MISSING=EXCLUDE: User-defined missing values are treated as missing.
	Cases Used	LISTWISE: Statistics are based on cases with no missing values for any variable used.
Syntax		<p>FACTOR</p> <p>/VARIABLES RISKNEED</p> <p>RISKPERCEPTION RISKTOLERANCE</p> <p>/MISSING LISTWISE</p> <p>/ANALYSIS RISKNEED RISKPERCEPTION RISKTOLERANCE</p> <p>/PRINT INITIAL KMO EXTRACTION</p> <p>ROTATION FSCORE</p> <p>/FORMAT SORT</p> <p>/PLOT EIGEN</p> <p>/CRITERIA FACTORS(3) ITERATE(50)</p> <p>/EXTRACTION PC</p> <p>/CRITERIA ITERATE(50) DELTA(0)</p> <p>/ROTATION OBLIMIN</p> <p>/METHOD=CORRELATION.</p>
Resources	Processor Time	00:00:00.187
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	Maximum Memory Required	1984 (1.938K) bytes

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.552
Bartlett's Test of Sphericity	Approx. Chi-Square	83.754
	df	3
	Sig.	.000

Communalities

	Initial	Extraction
RISKNEED	1.000	1.000
RISKPERCEPTION	1.000	1.000
RISKTOLERANCE	1.000	1.000

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	1.556	51.869	51.869	1.556	51.869
2	.887	29.575	81.444	.887	29.575
3	.557	18.556	100.000	.557	18.556

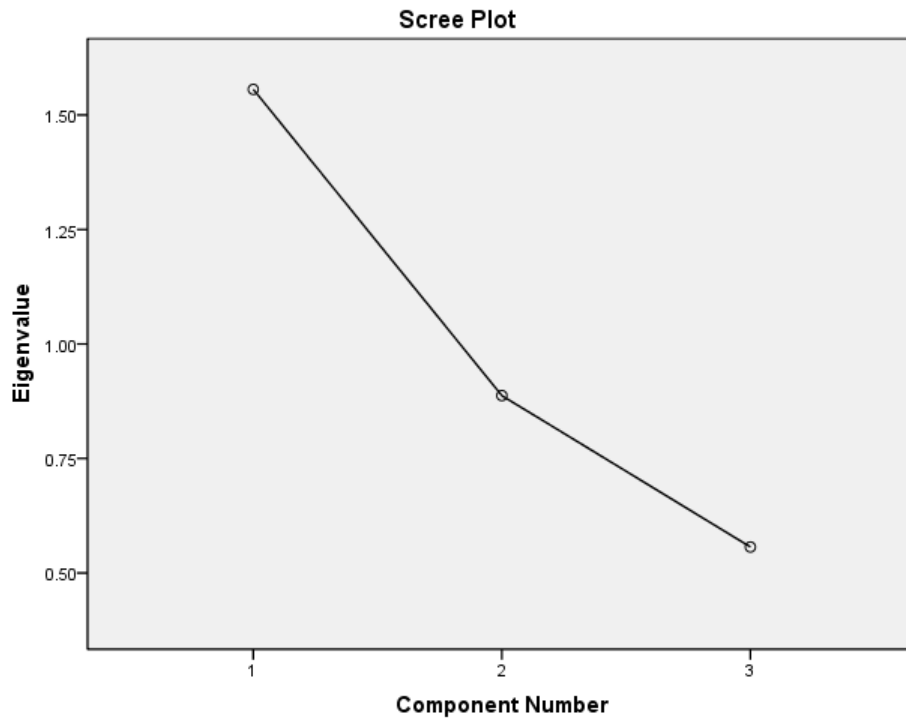
Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Extraction Sums of Squared Loadings	Rotation Sums of Squared Loadings ^a
	Cumulative %	Total
1	51.869	1.207
2	81.444	1.072
3	100.000	1.239

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.



Component Matrix^a

	Component		
	1	2	3
RISKTOLERANCE	.821	-.168	-.546
RISKNEED	.774	-.398	.493
RISKPERCEPTION	.533	.837	.125

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

Pattern Matrix^a

	Component		
	1	2	3
RISKNEED	1.000	.000	.000
RISKPERCEPTION	.000	1.000	.000
RISKTOLERANCE	.000	.000	-1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Structure Matrix

	Component		
	1	2	3
RISKNEED	1.000	.141	-.433
RISKPERCEPTION	.141	1.000	-.228
RISKTOLERANCE	.433	.228	-1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Correlation Matrix

Component	1	2	3
1	1.000	.141	-.433
2	.141	1.000	-.228
3	-.433	-.228	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Score Coefficient Matrix

	Component		
	1	2	3
RISKNEED	1.000	.000	.000
RISKPERCEPTION	.000	1.000	.000
RISKTOLERANCE	.000	.000	-1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Score Covariance Matrix

Component	1	2	3
1	.774	.152	1.506
2	.152	1.040	-.380
3	1.506	-.380	2.755

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

DESCRIPTIVES VARIABLES=CRP

/STATISTICS=MEAN STDDEV RANGE MIN MAX.

Descriptives

Notes

Output Created		12-Mar-2014 15:39:38
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.321.14.3.V ARIABLES.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=CRP /STATISTICS=MEAN STDDEV RANGE MIN MAX.
Resources	Processor Time	00:00:00.000
	Elapsed Time	00:00:00.000

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation
CRP	321	6.23	2.37	8.60	4.9798	1.12126
Valid N (listwise)	321					

CORRELATIONS

/VARIABLES=CRP VALIDITY
 /PRINT=TWOTAIL NOSIG
 /MISSING=PAIRWISE.

Correlations

Notes

Output Created		12-Mar-2014 16:53:35
Comments		
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	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics for each pair of variables are based on all the cases with valid data for that pair.

Syntax			CORRELATIONS
			/VARIABLES=CRP VALIDITY
			/PRINT=TWOTAIL NOSIG
			/MISSING=PAIRWISE.
Resources	Processor Time		00:00:00.016
	Elapsed Time		00:00:00.021

[DataSet1] D:\CARR.DISSERTATION.DATA.321.14.3.VARIABLES.sav

		CRP	VALIDITY
CRP	Pearson Correlation	1	.431**
	Sig. (2-tailed)		.000
	N	321	321
VALIDITY	Pearson Correlation	.431**	1
	Sig. (2-tailed)	.000	
	N	321	321

** . Correlation is significant at the 0.01 level (2-tailed).

SAVE OUTFILE='C:\Users\SVemuri\Documents\CARR.DISSERTATION.DATA.FINAL.sav'
/COMPRESSED.

SAVE OUTFILE='D:\CARR.DISSERTATION.DATA.FINAL.sav'
/COMPRESSED.

COMPUTE RISKFINAL=RISKNEED1 + RISKNEED2.
EXECUTE.

COMPUTE RISKPERCEPTIONFINAL=RISKPER1 + RISKPERF2.
EXECUTE.

COMPUTE RISKTOLERANCEFINAL=RISKTOL1 + RISKTOL2 + RISKPERF1 + RISKPER2.
EXECUTE.

COMPUTE CRPFINAL=(RISKNEED * .52)+(RISKPERCEPTION*.30) + (RISKTOLERANCE * .18).
EXECUTE.
FACTOR

```

/VARIABLES RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1
RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2
/MISSING LISTWISE
/ANALYSIS RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2
RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2
/PRINT INITIAL KMO EXTRACTION ROTATION FSCORE
/FORMAT SORT
/PLOT EIGEN
/CRITERIA FACTORS(7) ITERATE(50)
/EXTRACTION PC
/CRITERIA ITERATE(50) DELTA(0)
/ROTATION OBLIMIN
/METHOD=CORRELATION.

```

Factor Analysis

Notes

Output Created		12-Mar-2014 23:18:24
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.FINAL.sav
	Active Dataset	DataSet1
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	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
Missing Value Handling	Definition of Missing	MISSING=EXCLUDE: User-defined missing values are treated as missing.
	Cases Used	LISTWISE: Statistics are based on cases with no missing values for any variable used.

Syntax		<pre> FACTOR /VARIABLES RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2 /MISSING LISTWISE /ANALYSIS RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2 /PRINT INITIAL KMO EXTRACTION ROTATION FSCORE /FORMAT SORT /PLOT EIGEN /CRITERIA FACTORS(7) ITERATE(50) /EXTRACTION PC /CRITERIA ITERATE(50) DELTA(0) /ROTATION OBLIMIN /METHOD=CORRELATION. </pre>
Resources	Processor Time	00:00:00.327
	Elapsed Time	00:00:00.289
	Maximum Memory Required	25128 (24.539K) bytes

[DataSet1] D:\CARR.DISSERTATION.DATA.FINAL.sav

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.704
Bartlett's Test of Sphericity	Approx. Chi-Square	773.136
	df	91
	Sig.	.000

Communalities

	Initial	Extraction
RISKTOL1	1.000	.712
RISKTOL2	1.000	.607
RISKPER1	1.000	.775
RISKPER2	1.000	.910
RISKREF1	1.000	.536

RISKPREF2	1.000	.567
RISKCAP1	1.000	.680
RISKCAP2	1.000	.630
RISKCOMP1	1.000	.728
RISKCOMP2	1.000	.804
RISKKNOWL1	1.000	.882
RISKKNOWL2	1.000	.770
RISKNEED1	1.000	.749
RISKNEED2	1.000	.705

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance
1	2.989	21.349	21.349	2.989	21.349
2	1.778	12.701	34.051	1.778	12.701
3	1.329	9.491	43.542	1.329	9.491
4	1.122	8.011	51.553	1.122	8.011
5	1.047	7.482	59.035	1.047	7.482
6	.970	6.932	65.967	.970	6.932
7	.821	5.866	71.833	.821	5.866
8	.782	5.584	77.417		
9	.715	5.106	82.523		
10	.638	4.561	87.084		
11	.585	4.177	91.261		
12	.537	3.833	95.094		
13	.392	2.800	97.894		
14	.295	2.106	100.000		

Extraction Method: Principal Component Analysis.

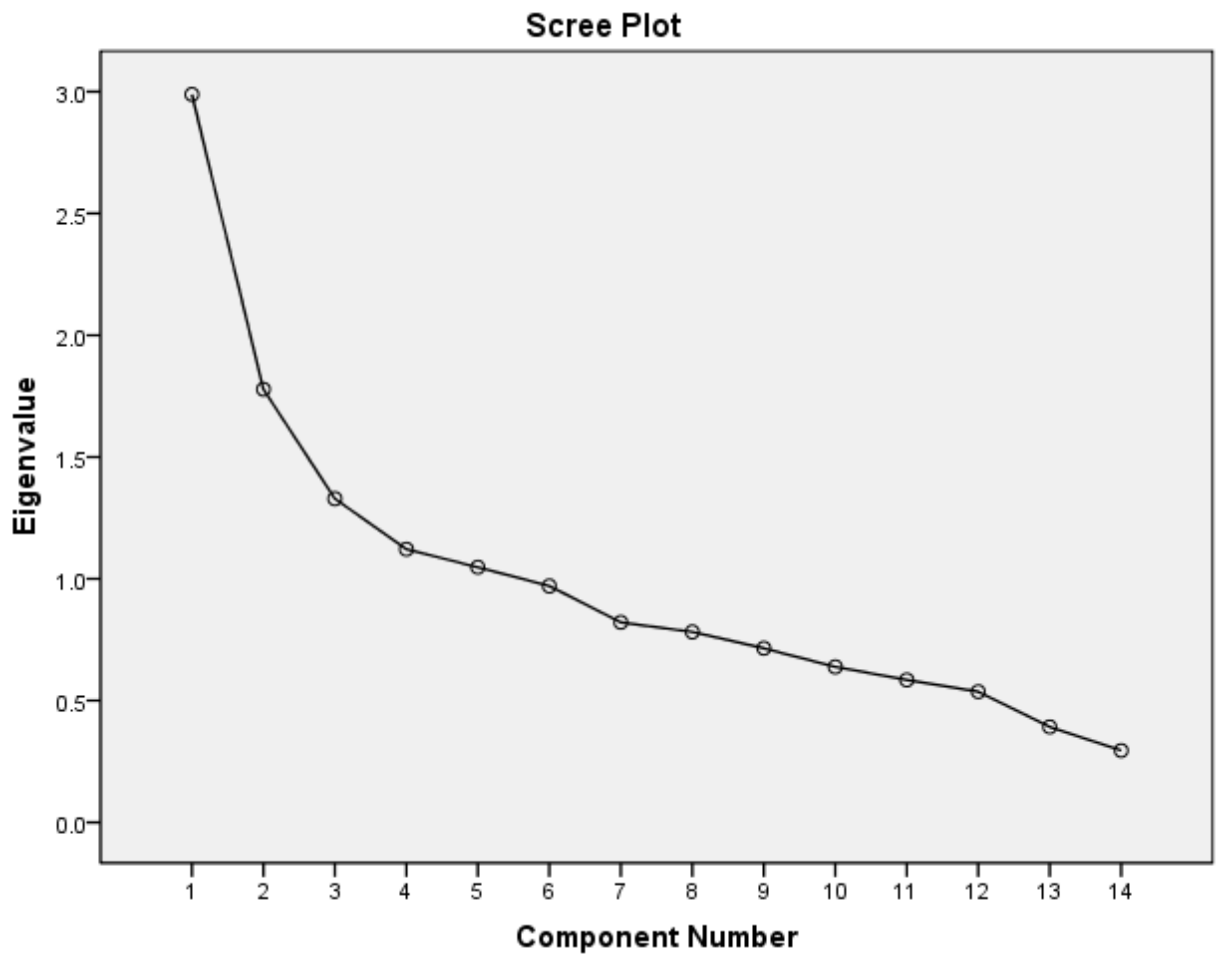
Total Variance Explained

Component	Extraction Sums of Squared Loadings	Rotation Sums of Squared Loadingsa
	Cumulative %	Total
1	21.349	2.625
2	34.051	1.836
3	43.542	1.335
4	51.553	1.261
5	59.035	1.164
6	65.967	1.316

7	71.833	1.372
8		
9		
10		
11		
12		
13		
14		

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.



Component Matrix

	Component

	1	2	3	4	5	6	7
RISKTOL1	.761	.073	.104	-.165	-.204	.029	-.219
RISKNEED1	.696	-.455	-.131	-.031	.162	-.025	.111
RISKTOL2	.690	.228	-.206	.044	-.139	.042	-.118
RISKNEED2	.673	-.452	-.127	-.104	.101	.107	-.012
RISKPREF1	.648	.196	.054	-.012	.245	-.094	-.069
RISKCAP1	.184	.666	-.037	-.221	-.122	-.107	-.355
RISKCAP2	.289	-.612	-.065	.296	-.273	-.044	-.063
RISKPER1	.178	-.092	.637	.067	.103	.557	.059
RISKKNOWL2	.199	.225	-.568	.347	.484	.018	-.052
RISKPREF2	.323	.226	.459	-.253	.370	.022	.003
RISKCOMP2	.098	.201	.363	.667	.306	-.277	.086
RISKCOMP1	.274	.248	.162	.530	-.515	.085	-.104
RISKKNOWL1	.140	.451	-.350	.050	-.089	.567	.453
RISKPER2	.424	.195	.119	-.161	-.231	-.466	.619

Extraction Method: Principal Component Analysis.

a. 7 components extracted.

Pattern Matrix

	Component						
	1	2	3	4	5	6	7
RISKNEED1	.849	-.136	.008	.038	.095	-.007	.119
RISKNEED2	.840	-.039	.082	-.099	.062	.001	-.015
RISKCAP2	.526	-.308	-.104	-.043	-.404	-.220	-.051
RISKPREF1	.406	.371	.097	.280	.086	.017	.113
RISKCAP1	-.230	.821	-.099	-.049	-.051	.004	.000
RISKTOL1	.492	.514	.164	-.138	-.213	-.056	.110
RISKTOL2	.432	.440	-.079	.033	-.238	.207	.066
RISKPER1	.063	-.145	.882	.023	-.105	.116	-.142
RISKPREF2	.067	.286	.483	.172	.327	-.077	.134
RISKCOMP2	-.151	-.127	.114	.859	-.196	-.142	.102
RISKKNOWL2	.259	.085	-.361	.505	.166	.354	-.293
RISKCOMP1	-.092	.170	.086	.173	-.804	.095	.038
RISKKNOWL1	-.063	-.077	.106	-.104	-.078	.958	.096
RISKPER2	.055	-.063	-.144	.046	.002	.100	.964

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 28 iterations.

Structure Matrix

	Component						
	1	2	3	4	5	6	7
RISKNEED1	.846	-.018	.071	.082	.004	-.008	.205

RISKNEED2	.827	.036	.123	-.045	-.022	.003	.098
RISKTOL1	.579	.566	.258	-.026	-.262	.031	.324
RISKCAP2	.511	-.334	-.082	-.090	-.461	-.264	-.038
RISKCAP1	-.151	.782	-.046	.049	-.013	.171	.133
RISKTOL2	.512	.534	-.019	.141	-.271	.318	.217
RISKPREF1	.475	.491	.185	.375	.051	.123	.278
RISKPER1	.099	-.069	.841	.055	-.115	.008	-.016
RISKPREF2	.121	.379	.547	.247	.315	-.045	.281
RISKCOMP2	-.072	-.019	.172	.825	-.178	-.104	.133
RISKKNOWL2	.233	.166	-.395	.537	.174	.476	-.290
RISKCOMP1	.028	.206	.110	.195	-.791	.125	.126
RISKKNOWL1	-.020	.129	.014	-.014	-.069	.915	.057
RISKPER2	.179	.171	.007	.095	-.051	.078	.933

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Correlation Matrix

Component	1	2	3	4	5	6	7
1	1.000	.101	.062	.065	-.097	.032	.138
2	.101	1.000	.085	.144	.019	.208	.221
3	.062	.085	1.000	.053	-.011	-.097	.166
4	.065	.144	.053	1.000	.016	.100	.054
5	-.097	.019	-.011	.016	1.000	.012	-.052
6	.032	.208	-.097	.100	.012	1.000	-.031
7	.138	.221	.166	.054	-.052	-.031	1.000

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Score Coefficient Matrix

	Component						
	1	2	3	4	5	6	7
RISKTOL1	.171	.311	.114	-.144	-.160	-.081	.059
RISKTOL2	.159	.252	-.085	.007	-.176	.149	.000
RISKPER1	.011	-.105	.691	.008	-.070	.098	-.104
RISKPER2	-.019	-.088	-.084	.026	.027	.044	.864
RISKPREF1	.150	.226	.068	.239	.133	.000	.066
RISKPREF2	.005	.196	.396	.158	.342	-.076	.132
RISKCAP1	-.119	.544	-.076	-.056	-.016	-.034	-.027
RISKCAP2	.221	-.226	-.109	-.061	-.385	-.178	-.063
RISKCOMP1	-.064	.066	.042	.086	-.702	.045	.006
RISKCOMP2	-.070	-.099	.084	.717	-.122	-.121	.096
RISKKNOWL1	-.027	-.097	.078	-.089	-.047	.802	.052
RISKKNOWL2	.136	.048	-.308	.455	.189	.324	-.316

RISKNEED1	.350	-.116	-.010	.041	.104	.003	.073
RISKNEED2	.347	-.047	.044	-.078	.067	.009	-.048

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

Component Score Covariance Matrix

Component	1	2	3	4	5	6	7
1	1.141	.560	2.005	.320	.338	2.090	1.485
2	.560	1.197	.366	.311	2.028	.510	.895
3	2.005	.366	3.174	.491	1.432	2.045	3.519
4	.320	.311	.491	1.110	.284	1.258	.313
5	.338	2.028	1.432	.284	4.033	.482	.965
6	2.090	.510	2.045	1.258	.482	4.058	.694
7	1.485	.895	3.519	.313	.965	.694	3.116

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

RELIABILITY

```

/VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1
RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2
/SCALE('7-FACTOR CONSTRAINED MODEL') ALL
/MODEL=ALPHA
/STATISTICS=SCALE.

```

Reliability

Notes

Output Created		12-Mar-2014 23:19:23
Comments		
Input	Data	D:\CARR.DISSERTATION.DATA.FINAL.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	321
	Matrix Input	
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.

Syntax	Cases Used	Statistics are based on all cases with valid data for all variables in the procedure. RELIABILITY /VARIABLES=RISKTOL1 RISKTOL2 RISKPER1 RISKPER2 RISKREF1 RISKREF2 RISKCAP1 RISKCAP2 RISKCOMP1 RISKCOMP2 RISKKNOWL1 RISKKNOWL2 RISKNEED1 RISKNEED2 /SCALE('7-FACTOR CONSTRAINED MODEL') ALL /MODEL=ALPHA /STATISTICS=SCALE.
Resources	Processor Time Elapsed Time	00:00:00.016 00:00:00.010

[DataSet1] D:\CARR.DISSERTATION.DATA.FINAL.sav

Scale: 7-FACTOR CONSTRAINED MODEL

Case Processing Summary

		N	%
Cases	Valid	321	100.0
	Excluded ^a	0	.0
	Total	321	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.590	14

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
33.9938	24.581	4.95794	14

Nicholas Carr, Ph.D. Candidate, CIMA®

nickcarr@ksu.edu

(239) 273-8838

OBJECTIVE

Pursue a career in retail wealth and investment management, and contribute to academia through research and instruction. My primary career intention is to continue to assist families and institutions with their holistic wealth management, financial planning, and investment management needs. I am also very passionate about pursuing opportunities within academia, such as but not limited to, research and instruction at the collegiate level.

WORK EXPERIENCE

- 02/2011-CURRENT The Legates Carr Wealth Management Group, Merrill Lynch
Vice President, Wealth Management Advisor, PIA Portfolio Manager
- Provide high net worth clients with holistic wealth management services.
 - Primary responsibilities include wealth/portfolio management and financial planning for a fee-based practice of approx. \$210 million
- 04/05-02/2011 Charles Schwab Private Client
Vice President, Financial Advisor
- Provide high net worth clients with holistic wealth management.
 - Primary responsibilities included wealth/portfolio management and financial planning for a fee-based practice of \$150 million, and transition self-directed investors into the advisory program.
- 04/04-01/05 Bank of America Wealth & Investment Management
Assistant Vice President, Premier Bank Client Manager
- Provide high net worth clients with full-service wealth management strategies by analyzing their finances and providing customized solutions.
 - Facilitate a team of financial experts to provide clients with a variety of financial services.
- 06/02-04/04 Wachovia Securities/ National Bank
Finance Specialist
- Full – service financial services for clients of the bank.
 - Other roles included analyzing current/past micro and macro economic conditions, analyzing equity and debt markets, business acquisition, and managing client assets and liabilities of the bank of over \$75 million.
- 02/00-06/02 Morgan Stanley
Financial Advisor
- Main objective was assisting clients/prospects with full-service financial planning with one of the top asset management firms.

- Other roles included analyzing market conditions and prospecting/networking for new business.

Fauquier County Office of Management & Budget

Intern

12/98-12/2000

- Assisted budget director with preparation of annual budget.
- Assisted Virginia Tech professor with a comprehensive economic fiscal impact model.

EDUCATION

Kansas State University, College of Human Ecology	Manhattan, KS
<ul style="list-style-type: none"> ■ 2009- Present, PhD Candidate, Personal Financial Planning	
Indiana University, Kelley School of Business	Bloomington, IN
<ul style="list-style-type: none"> ■ 2006, M.S. Finance 	
Virginia Tech, Pamplin School of Business	Blacksburg, VA
<ul style="list-style-type: none"> ■ 2001, B.S. Finance, Minor, Economics 	

FINANCIAL CERTIFICATIONS/LICENSES

- CIMA (Certified Investment Management Analyst)
- Merrill Lynch PIA Portfolio Manager
- Series 7
- Series 66
- Series 31
- Life, Health, and Variable Insurance

PROFESSIONAL/COMMUNITY MEMBERSHIPS

- IMCA (Investment Management Consultants Association), Member
- FPA (Financial Planning Association)
- FSP (Financial Services Professional), Member, Contributing author
- ACCI (American Council on Consumer Interests)
- SOME (So Others Might Eat)

- NFL Players' Association, Registered Financial Advisor
- USTA (United State Tennis Association), Member (4.5 & Men's 35 & Under Level Florida Top 25 Player) and Community Sponsor

AWARDS/RECOGNITION/PUBLICATIONS/PRESENTATIONS/TEACHING/SPEAKING

- Instructor, FSHS 300, Behavioral Finance, Kansas State University 2010-Present
- Instructor, FSHS 101, Money 101, Kansas State University 2013- Present
- Published work, January 2013, *Journal of Financial Services Professionals*, with Dr. John Grable, Goals-Based Financial Planning & Risk Tolerance
- Paper Presentation, Sensation Seeking & Risk Tolerance with Dr. John Grable, ACCI Annual Conference, 2011
- Paper Award: Consumer Economics, Sensation Seeking & Risk Tolerance, ACCI Annual Conference, 2011
- Paper Presentation, The Relationship Between Health and Wealth, ACCI Annual Conference, 2012
- Speaker, Behavioral Finance and Risk Assessment, FPA of Kansas City, October 2011 Conference
- Speaker, Behavioral Finance, FPA of South Korea, Summer 2012
- Merrill Lynch Team of the Year, 2014, SWFL Market
- Gulfshore Life Magazine's Top Wealth Advisor List, 2008-2014
- Merrill Lynch Executive Club Member, 2011-present
- Charles Schwab Private Client Southern Region Top 25 Producer in Advisory Service Revenue, 2008-2010