ANALYSIS OF AFFECT ASSOCIATED WITH FINANCIAL RISK TOLERANCE

by

ABED GOLAM RABBANI

(Under the Direction of John Grable)

ABSTRACT

This study developed and empirically tested a model using risk tolerance and demographic data from the Rutgers New Jersey Agricultural Experiment Station Investor Risk Tolerance database. The purpose of this study was to develop a methodology to estimate affect (i.e., feelings), use affect to describe investors, and to determine the degree to which affect measure is associated with investor's portfolio risk. A survey created by Grable and Lytton (1998) was used to estimate subjective evaluation (*SE*) and objective evaluation (*OE*). Two theories Risk-as-Feelings (RaF) hypothesis and Classical Test Theory (CTT) were utilized to guide the estimation of affective evaluation (*AE*) score and development of *AE* groups. There were two components in *GL-FRT*. One component was composed of nine cognitive assessment items that were the indicators of *OE*. One item was chosen as an indicator of *SE*. A differential prediction model demonstrated that respondents did exhibit *AE* as suggested by the RaF hypothesis. A series of statistical analyses using chi-square tests of homogeneity of demographic characteristics for each *AE* group, an ordinal regression analysis of demographic characteristics as a predictor of *AE* groups, and a cluster analysis using *AE* groups and demographic characteristics showed that demographic characteristics were not good descriptors of *AE* groups. Finally, the findings of an OLS regression analysis of *AE* groups and *PR* scores controlling for the demographic variables and reliance on professional advice showed that *AE* group was associated with *PR* scores. This study showed that the error associated with *FRT* estimation is an indicator of affect and that affect is measurable using *AE*. The findings from this study provide financial planners a tool for estimating affect (i.e., *AE*). This tool is also helpful for investors who are increasingly responsible for their own investment decisions. As financial planners are responsible for understanding individual attitudinal differences to determine the appropriate portfolio for their clients, they may use these findings to assist clients make decisions that will help in wealth generation and fulfilling their financial goals.

INDEX WORDS: Risk as Feelings, Affect, Subjective evaluation, Objective evaluation, Affective evaluation, Differential Prediction

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DEDICATION

I dedicate this thesis to my father and mother whose affection, love, encouragement and prayers make me able to be where I am now. They sacrificed so that I can fulfill my dream. They taught me righteousness and patience, two most precious quality one can ask for.

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TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Introduction and Statement of the Problem

Financial risk tolerance (*FRT*) is generally defined as the maximum amount of risk or uncertainty an individual is willing to accept when making a financial decision (Grable, Britt, & Webb, 2008).There is evidence to suggest that nearly all individuals inaccurately gauge their level of *FRT* to some extent. For example, Hsee and Weber (1997) observed that people tend to underestimate their own risk tolerance systematically when compared to hypothetical others. Hallahan, Faff, and McKenzie (2004) compared self-estimated risk tolerance to a score on a 25-item risk-tolerance scale. Results from their study indicated that 73% of respondents underestimated, while only 23% overestimated and 4% accurately estimated their subjective risk tolerance. Moreschi (2005), using a 25-item scale, also reported a similar result. Geoff Davey, the co-founder of FinaMetrica – a firm that markets a risk-profiling system – argued in an interview with *Money* magazine, “People underestimate risk when markets are booming and overestimate it when there’s a bust” (Updegrave, 2013, p.1). This observation assumes that people misjudge their risk tolerance; as such, they make an error in their subjective evaluation of risk. The issue then is that overestimation or underestimation of *FRT* may lead an investor to engage in suboptimal investment decision making.

There are many factors that need to be examined in order to implement an optimal investment regimen, one that focuses on the investor’s objectives, applies an asset-allocation strategy that is appropriate for the investor, and puts the investor on track to reach his or her financial goals. Among those factors, *FRT* is surely a factor that is central to the investment decision process (Hanna, Waller, and Finke, 2008). Financial planners manage the financial resources of individuals and families. Some key characteristics of this service are that it is not only a value-driven process but also a goal-driven process (Lytton, Grable, & Klock, 2013). Putting together a diversified investment strategy that fits a person's tolerance for risk takes some reflection and thoughtful analysis. In order to achieve desired goals, financial planning should be carried out on a continuing basis to account for new products, changes in the financial markets, and changes in personal situation. For the well-being of a client, it is important for a financial planner not only to assess his or her client's risk tolerance accurately, but also to ensure that an assessment outcome agrees with a client's own perception of risk tolerance (Lucarelli & Brighetti, 2011). In particular, when financial planners are providing investment advice for a fee, they are bound to follow a fiduciary standard that requires them to put their clients' interests above their own (Gilliam, Chatterjee, & Grable, 2010a). By definition, for a planner, a client's risk tolerance is a key factor used to make investment choices.

The systematic overestimation or underestimation of *FRT* by an individual compared to an independent criterion is known as Risk Tolerance Estimation Error (*RTEE*) (Grable & Roszkowski, 2007). *RTEE* (i.e., a positive or negative deviation from an objective score) is calculated by evaluating subjective risk-tolerance scores compared to objectively measured risk-tolerance. Although there are several studies that have explored estimation error in *FRT*, the focus in scholarly contributions has been limited to considering the role demographic characteristics play in making inaccurate subjective assessments.

Several demographic variables have been found to be significantly related to *RTEE*: gender (Gilliam & Grable, 2010; Grable & Roszkowski, 2007), age (Gilliam & Grable, 2010; Grable, McGill, & Britt, 2009a), educational status (Gilliam & Grable, 2010), and marital status (Gilliam & Grable, 2010; Grable et al., 2009a). Grable and Roszkowski (2007), for example, found that women systematically underestimate their psychometrically measured risk tolerance while men overestimate their tolerance for risk. Grable et al. (2009a) noted that younger working adults tend to overestimate their risk tolerance compared to older working adults. They also found that married individuals tend to underestimate their risk tolerance compared to singles. For financial planners who advise clients on how best to save, invest, and grow their money, this estimation error can be misleading and may lead to suboptimal investment decisions.

Dunning, Griffin, Milojkovic, and Ross (1990) noted that people's confidence in their subjective assessment of a situation greatly surpasses their objective accuracy. They explained that people interpret an uncertain situation based on their available knowledge and experience. It is difficult to alter an initial interpretation, and as a result, future assessments or evaluations tend to follow the initial interpretation. It is probable that someone who uses their knowledge and experience to initially over- or underestimate the variability in a situation is likely to carry this estimation error into assessments of their own feelings and attitudes about risk scenarios (Grable et al., 2009a). Further, people tend to rely on heuristic judgments, which almost always lead to inconsistency in estimations (Heisler, 1994; Roszkowski & Grable, 2005). Therefore, estimation errors with a risk-tolerance assessment may be a manifestation of a combination of analytical miscalculations and experiential feelings.

Recent developments in the financial planning and economics literature indicate that an assessment of risk may be associated with both an individual's analytical system and experiential system of risk appraisal (Damasio, 1994; Dillard, Ferrar, Ubel, & Fagerlin, 2012; Galentino & Bonini, 2014; Loewenstein, Weber, Hsee, & Welch, 2001; Slovic, Finucane, Peters, & MacGregor, 2004; Wang, Zhang, & Tuo, 2014). As Epstein (1994) observed, "There is no dearth of evidence in everyday life that people apprehend reality in two fundamentally different ways, one variously labeled intuitive, automatic, natural, non-verbal, narrative, and experiential, and the other analytical, deliberative, verbal, and rational" (p. 710). Loewenstein et al. (2001) parsimoniously formalized this dual process of decision-making under risk in their Risk-as-Feelings (RaF) hypothesis and documented that risk perceptions are influenced by association-driven and affect-driven processes (i.e., experiential system) as much or more than by rule-based and reason-based processes (i.e., analytical system). "Such cognitive evaluations have affective consequences, and feeling states also exert a reciprocal influence on cognitive evaluations" (Loewenstein et al., p. 270). The RaF hypothesis model suggests that emotions often overcome rationality when people make decisions under uncertainty. Thus, decision making behavior depends not only on an objective evaluation which is a cognitive response, but also on affective response. Slovic et al, (2004) defined affect as "The specific quality of goodness or badness (a) experienced as a feeling state (with or without consciousness) and (b) demarcating a positive or negative quality of a stimulus" (p. S36). It is, therefore, reasonable to hypothesize that estimation error in *FRT* may be a result of affective responses.

Loewenstein (2000) argued that immediate feelings (i.e., affect) experienced at the time of making a decision "often propel behavior in directions that are different from that directed by a weighing of the long-term costs and benefits of disparate action" (p. 426). Slovic et al. (2004)

argued that intuition, instinct, and gut feelings were used to make decisions under uncertainty before there was probability theory, risk assessment, and decision analysis. Xiao, Sorhaindo, and Garman (2006) reported that a reduction in financial stress among consumer credit counseling clients was associated with future constructive financial behaviors. Porcelli and Delgado (2009) confirmed the negative impact of stress on a person's ability to make financial decisions. Based on this evidence, it is reasonable to hypothesize that affect plays a central role in the dual-process theories of thinking, knowing, and information processing.

Holtgrave and Weber (1993) noted that affective reactions play a crucial role even in seemingly "objective" contexts, such as financial investment decisions. In nearly all risk-tolerance measures, researchers include questions related to attitudes, current behavior, and experience (Carr, 2014; Grable & Joo, 2004; Grable & Lytton, 2001; Roszkowski, Davey, & Grable, 2005; Roszkowski & Grable, 2005) in order to account for the influence of experiential systems (i.e., affect). Take for example, the following item from the Grable and Lytton (*GL-FRT*) risk scale that asks: "When you think of the word "risk" which of the following words comes to mind first? (a) Loss, (b) Uncertainty, (c) Opportunity, and (d) Thrill." This item can be used to assess the experiential and knowledge dimension of financial risk-tolerance (Grable & Lytton, 1999).

Affect, which is defined as the specific quality of goodness or badness of a situation or event, may alter the way a person perceives a financial risk. Affect perception can also shape a person's willingness to take risk. Thus, affect may have an impact on a person's evaluation of their own risk tolerance and may lead to estimation error. However, conducting a study on affect and tolerance for financial risk has several challenges. First, it is difficult to quantify and estimate affect or feelings, and second, it is difficult to find data where affect or feelings is measured. This study aims to address the issue of estimating affect or feelings by analyzing estimation errors associated with *FRT* from a RaF hypothesis perspective. In this study, *RTEE* is analyzed as affect that is hypothesized to have a positive or negative influence on an investor's subjective risk-tolerance assessment.

1.2 Purpose and Justification of Study

Financial planners are well aware of the significance of risk tolerance in the context of investment decisions. Nevertheless, there is little understanding of how the concept of affect may explain inaccuracies in the subjective evaluation (*SE*) of risk tolerance. Investors are likely to differ in their investment behavior depending on whether their affective evaluations (*AE*) positively or negatively influence their objective evaluations (*OE*). The main purpose of this research is to develop a methodology to estimate affect or feelings as a component of a person's tolerance of risk, and use the estimate to describe investors and understand differences in their investment behaviors (e.g., portfolio risk).

Relying on the RaF hypothesis and Classical Test Theory (CTT), this study quantifies the level of affect using *RTEE*. A series of statistical analyses were used to investigate if it is possible to describe the demographic characteristics of investors with similar level of affect (i.e., *AE*). There is some literature that illustrates the ways demographic characteristics are associated with risk tolerance (Cooper, Kingyens, & Paradi, 2014) and *RTEE* (Grable, 2008). However, these findings are by no means conclusive. This study further analyzed the association between affect and risk observed in investor's portfolio.

The findings of this study may help a financial planning practitioner by describing a tool to asses affect associated with a client's *FRT* estimation. The results can be used to provide a description of investors based on recent theoretical developments in risk research, such as the RaF hypothesis. Dividing investors into groups of similar *AE* may assist practitioners to better understand a client's portfolio risk. The study adds to the current understanding of *FRT* by estimating affect and taking affective processes into consideration as a tool for making an inclusive judgment about estimation errors associated with risk-tolerance assessment.

1.3 Background

1.3.1 Financial planning process. Risk tolerance is a crucial factor that influences a wide range of personal financial decisions (Snelbecker, Roszkowski, & Cutler, 1990). The debt versus savings decision individuals regularly make, the type of mortgage selected, and the use and management of credit cards are examples of situations where a person's *FRT* can influence behavior (Campbell, 2006). Risk tolerance is also an underlying factor within financial planning models, investment suitability analyses, and consumer decision frameworks (Grable, 2008). The literature shows, for example, that if a client's *FRT* is not accurately assessed this may equally result in missed goal achievement.

Personal financial planning is a value and goal driven approach that uses strategic planning in its core structure (Overton, 2008). Financial planning practice utilizes Certified Financial Planner Board of Standards, Inc. (CFP Board) (2016)'s process of financial planning, which some researchers (e.g., Overton, 2008) consider an extension of the theory of strategic planning. The financial planning model includes the following six steps:

(1) Initial meeting with the client. This is also known in the profession as the “Initial Consultation” (IC). This step is required to build trust and mutual understanding.

(2) Gather client information. This step is very important to gather not only a client’s financial information but also client goals, values, risk tolerance, time perspective, objectives, savings behavior, and other factors.

(3) Data analysis and synthesis. This is an exclusive stage where running models, time value of money analyses, triangulation, and scenario analyses are conducted given a client’s situation.

(4) Recommendation. At this stage, the financial planner recommends one or more actions. Some revision of previous recommendations is also expected at this step in the process.

(5) Implementation. With a client’s approval, the financial planner finalizes an implementation checklist in precise detail (i.e., what, who, when, where, how) (Lytton et al., 2013) and puts recommendation into practice

(6) Monitoring and evaluation. In a specific agreed upon interval, the financial planner reviews, evaluates, and makes necessary updates to the plan.

The financial planning process is dynamic in nature, which has long-term implications for clients. Since the initial conceptualization of the strategic planning process, the approach has evolved over time to what is generally known as strategic management (Mintzberg, 1994), and finally, to strategic thinking (Liedtka, 1998). In explaining the difference between strategic planning and strategic thinking, Mintzberg (1994) argued that strategic planning is the systematic programming of pre-identified strategies from which an action plan can be developed. Strategic thinking, on the other hand, is a synthesizing process utilizing intuition and creativity. As strategic planning has evolved to strategic thinking, financial planning processes have also evolved (Overton, 2008).

The practice of financial planning relies on different aspects of strategic thinking (Overton, 2008). Strategic thinking is defined as an individual's capacity for thinking conceptually, imaginatively, systematically, and opportunistically with regard to the attainment of success in the future (Liedtka, 1998). As shown in Figure 1.1, there are five characteristics that define strategic thinking: (a) a system or holistic view; (b) a focus on intent; (c) thinking in time; (d) being hypothesis-driven; and (e) being intelligently opportunistic. Financial planning meets and encourages many of these criteria.

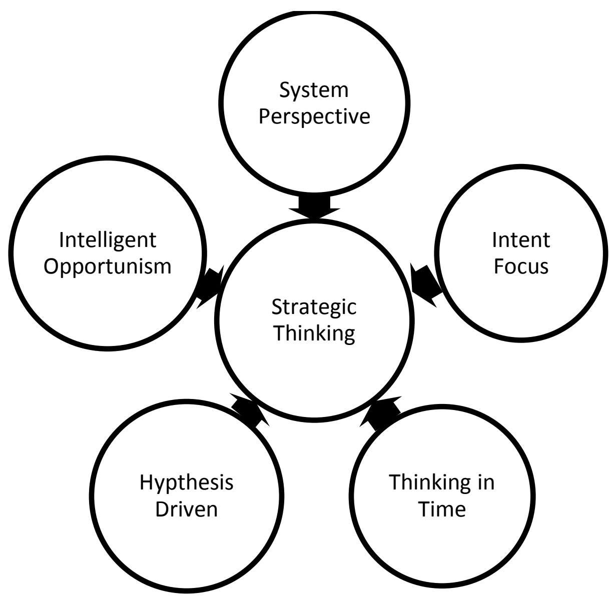

Figure 1.1. The elements of strategic thinking (Liedtka, 1998).

Strategic thinking employs mental processes that are conceptual (i.e., abstractions, using analogy to translate across contexts), systematic (i.e., composed of different components with interfaces that interact to produce intended or emergent behaviors, pattern finding, and connecting situations that are not obviously related), imaginative (i.e., creative and visual), and opportunistic (i.e., searching for and grasping new information and value propositions). It is important for a financial planner to apply these processes in their orientation towards future client success. Each planner and client has a different set of experiences and perspectives. The challenge is to bring together experience, perspective, and individual insight into a synthesized understanding of the situation and the need for coordinated actions.

Strategic thinking is an intuitive and creative process. It requires a planner to look for ingenious and innovative ways to achieve client goals (Liedtka, 1998). It is not only knowledge, but also a creative use of that knowledge that helps clients achieve their goals (Overton, 2008). Intuitive activities are associated with the experiential system (Epstein, 1994; Slovic et al., 2004) or the affect-driven process (Loewenstein et al., 2001). Thus, understanding the influence of affect is important for the continued evolution of financial planning from a strategic planning model to strategic thinking approach.

In financial planning, achieving client goals and objectives is associated with the accurate assessment of a client's *FRT*. CFP Board (2014) Practice Standard 200-1 states, "Goals and objectives must be consistent with the client's values and attitudes in order for the client to make the commitment necessary to accomplish them." Leimberg, Satinsky, Doyle, and Jackson (2012) argued that in order to understand a client situation, a financial planner should assess a client's risk tolerance.

Many times, it is a challenge for a financial planner to gauge a client's risk tolerance accurately and match this to recommendations to help a client achieve their goals and objectives because decision choices vary with affective reactions at the moment of choice (Loewenstein, 2000). For instance, people often make sub-optimal decisions when they are in a bad mood. Moreover, several factors are associated with *FRT*. Leimberg et al. (2012) identified 16 variables that influence risk tolerance. Later, Grable and Lytton (2003) reduced this number to the following being of particular importance: gender, age, marital status, education, and income. As noted by these authors, the influence of demographic factors and affect further complicates a financial planner's work.

1.3.2 Risk-as-Feelings hypothesis and financial planning. Currently, there are a wide variety of theoretical models used in the literature to explain and predict risk tolerance. These conceptualizations can be classified as either normative or descriptive. Normative theories explain how someone should respond in a given situation. Expected utility based models, such as Modern Portfolio Theory (MPT) (Markowitz, 1952) and the Capital Asset Pricing Model (CAPM) (Sharpe, 1964), are examples of normative risk theories. Descriptive theories explain how someone responds in a given situation in actuality. These methods typically incorporate psychological constructs to explain economic behavior. Prospect theory (Kahneman & Tversky, 1979) is a descriptive theory that has become a dominant framework for risk tolerance research. However, Loewenstein et al. (2001) criticized descriptive theories for being consequential in nature. They argued that consequential approaches are based on the assumption that decision making behavior is an objective process where an individual makes an objective evaluation of decision alternatives based on subjective probabilities and anticipated outcomes. Loewenstein et al. provided evidence that emotional reactions to risky situations often diverge from their objective assessments and proposed an alternative model called the Risk-as-Feelings (RaF) hypothesis. A new stream of studies has relied on the RaF concept, which has now become a common research paradigm (Lucarelli & Brighetti, 2011). The RaF hypothesis model posits the notion that emotions often overcome rationality when people make decisions under uncertainty (Damasio, 1994; Loewenstein, 2000; Peters & Slovic, 2000). According to this paradigm, decision making behavior depends not only on an objective evaluation, but also on affective processes. The basic premise of the RaF hypothesis is that *OE* and *AE* influence each other as shown in Figure 1.2. Loewenstein (2000) argued that people assess the desirability and likelihood of possible outcomes of choice alternatives and integrate this information into some type of expectation-based calculus to arrive at a decision. Therefore, affective processes may explain why many investors either overestimate or underestimate their tolerance for risk at any given time.

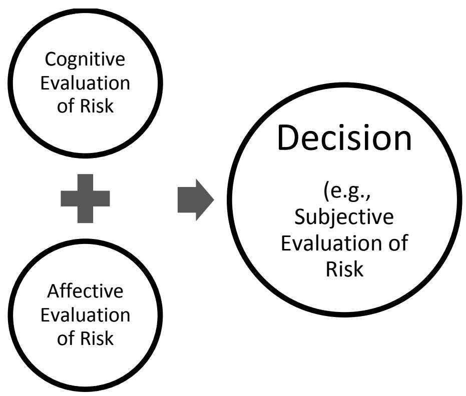

Figure 1.2. Three major elements of risk described in the RaF hypothesis.

1.3.3 Conceptual framework for estimating affective evaluation. Strategic thinking, as proposed by Liedtka (1998), provides a background for describing possible ways to incorporate intuitive, experiential, fast, and imaginative processes, like affect, into financial planning decision-making models. The RaF hypothesis provides a framework for estimating *AE* in financial planning.

The following conceptual framework provides a layout for quantifying *AE* as it relates to *FRT* assessment. This study intends to extend the RaF hypothesis by documenting that affect associated with financial risk appraisal may be quantifiable through the use of Classical Test Theory (CTT).

The modern model of CTT was introduced by Lord, Novick, and Bimbaum (1968). CTT provides a general framework linking observable variables to unobservable variables. At its core, CTT is premised on the notion that nearly all attitudinal constructs can be measured with three elements: (a) an observed score (*OS*), (b) a true score (*TS*), and (c) measurement error (*ME*). The CTT formula is:

$OS = TS + ME$……………………………(i)

CTT functions under some simplifying assumptions: (a) true scores and error scores are uncorrelated; (b) the average error score in the population is zero; and (c) error scores on parallel tests are uncorrelated. There are different formulations of this model. In one formulation, error scores are defined; in this case, the true score is the difference between an observed score and an error score. In another formulation, the true score is defined as the expected test score over parallel forms. In either case, the resulting model is the same; however, some researchers prefer the later formulations because these result in defining a true score, rather than having it obtained as the difference between an observed score and an error score (Hambleton & Jones, 1993).

Within CTT, *ME* is thought to be a function of two factors: systematic (e_s) and random error (e_u). Systematic error is defined as an error that is not determined by chance but is introduced by an inaccuracy inherent in the system. For instance, if there is loud traffic noise outside of a classroom where students are taking a test, this noise is liable to impact all of the children's scores, thus systematically lowering all scores uniformly. Unlike random error, systematic errors tend to be consistently either positive or negative. That is why systematic error is sometimes considered to be a bias in measurement. Random error, on the other hand, refers to a particular component of error that has no statistical predictability. Ott (1993) defined random error as the component that “takes into account all unpredictable and unknown factors that are not included in the model” (p. 440). Random error is caused by any factor that randomly influences measurement of the variable across the sample. For instance, a person's mood can inflate or deflate their performance on an occasion (Apergis & Voliotis, 2012). In a particular testing situation, some children may experience a good mood while others may be depressed. If a good or bad mood impacts their performance on the measure, it may artificially inflate the observed scores for some children and artificially deflate scores for others. The important thing about random error is that it does not have consistent effects across the entire sample. Instead, it pushes observed scores up or down randomly. In effect, CTT suggests that, by definition, as measurement error increases, there is an increased amount of variability in an attitudinal assessment’s observed score. This assumes, of course, that the true score is an accurate representation (i.e., both valid and reliable) of a person’s attitudinal assessment.

This research study utilized CTT as a framework to evaluate the role of feelings within the RaF hypothesis. The framework is premised on the assumption that a person’s subjective evaluation (*SE*) of risk tolerance can be used as an indicator of their observed score. Grable, Roszkowski, Joo, O’Neill, & Lytton (2009b) noted that it is conceivable to measure *SE* through a risk-assessment item such as: “In general, how would your best friend describe you as a risk taker?” In fact, the Federal Reserve Board has used a single risk-evaluation question, the Survey of Consumer Finances, for nearly three decades. In this study, a key proposition is: $SE = OS$. Additionally, a key assumption in the framework is that an objective evaluation (*OE*) can serve as a proxy for a true score, where *OE* = *TS*. Guillemette and Finke (2014) argued that a valid and reliable scale can be used as an indicator of a person's *OE*. As such, it is possible to recharacterize CTT (Equation (*i*)) as follows:

$$SE = OE + (e_s + e_u) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (ii)$$

where, *SE* = subjective evaluation of risk tolerance, *OE* = objective evaluation of risk tolerance, e_s = systematic error, and e_u = random error.

There is evidence in the literature that the level of measurement error is more than trivial as it relates to *FRT* (Hallahan et al., 2004; Moreschi, 2005). Consider Figure 1.3 from Grable and Rabbani (2014). The figure represents differences between *SE* and *OE* among a diverse group of pre-retiree Americans. Differences in scores represent some form of measurement error on the part of survey participants. Someone whose score falls on the left side of the mean (0) is thought to underestimate their tolerance for risk, whereas a score to the right indicates an overestimation. While the majority of people do tend to be relatively accurate in their risk appraisal, there are some who fall into the extremes.

The errors associated with assessment, as shown in Figure 1.3, are likely due to discrepancies in each person's analytical system and experiential system of risk evaluation (Epstein, 1994; Finucane, Slovic, Mertz, Flynn, & Satterfield, 2000; Loewenstein et al., 2001; Slovic et al., 2004). For example, people who read sad news articles are known to give higher risk estimates for a variety of risk domains (e.g., floods, disease, etc.) than people who read happy news accounts (Johnson & Tversky, 1983). Fearful individuals make relatively pessimistic

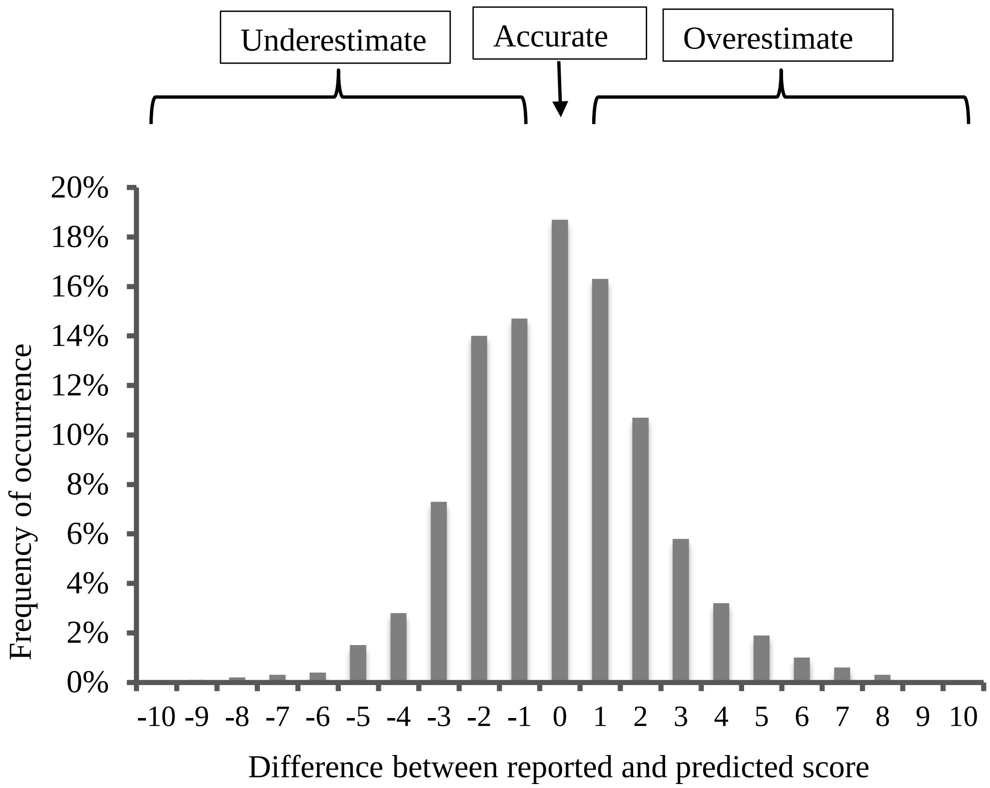

Figure 1.3. Accuracy of risk-tolerance estimation frequency (Grable & Rabbani, 2014).

risk assessments and relatively risk-averse choices (Lerner & Keltner, 2000). Based on the previous literature, it is reasonable to make the following propositional assertions:

(a) the analytic system is less efficient when used alone rather than in combination with the experiential system;

(b) the analytic and the experiential systems operate in parallel (Slovic et al., 2004);

(c) the analytic system uses algorithm and normative rules, such as probability and formal logic;

(d) *OE*, as defined above, can reasonably be conceptualized as a proxy for the analytic system (Slovic et al., 2004);

(e) the experiential system is intuitive and mostly automatic;

(f) e_u, as a component of measurement error, can represent the experiential system (e.g., mood); and

(g) e_s, as a component of measurement error, can represent the systematic error due to cognitive bias (e.g., overconfidence).

In this study, the experiential system (e_u) is defined as an indicator of affect within the RaF hypothesis (Finucane et al., 2000). This is termed as affective evaluation (*AE*). Therefore, it is possible to reframe Equation (*ii*) as follows:

$$SE = OE + (AE + e_s)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(iii)$$

where, *SE* = subjective evaluation, *OE* = objective evaluation, *AE* = affective evaluation (i.e., e_u = *AE*), and e_s = systematic error. If affect is an experienced state indicating a positive or negative quality of arousal (Slovic et al., 2004), and e_s is the systematic error associated with cognitive bias (Barber & Odean, 2001; Grable et al., 2009b; Wood & Zaichkowsky, 2004), then

$$AE = -e_s\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(iv)$$

When,

$$SE = OE$$

That is, when a subject's objective evaluation (i.e., analytic system) is perfectly aligned with their subjective evaluation, the subject can be said to have arrived at an objective evaluation devoid of affect and cognitive bias. When $OE \neq SE$ then the subject is thought to incorporate feelings and/or cognitive bias into the evaluation process. As such, if data for both *OE* and *SE* can be gathered from a subject, it may be possible to estimate the level of affect being used by that individual when conceptualizing *FRT*. In terms of measurement, it is possible to evaluate both *SE* and *OE*, and as such, *AE*.

Additionally, *SE*, *OE*, and *AE* are hypothesized to be influenced by each subject's preferences, perceptions, and capacity to take a financial risk. *SE* itself is hypothesized to be influenced by other factors beyond evaluation, including the demographic profile of a subject (Loewenstein et al., 2001). *AE* is known to depend on characteristics of the individual (Gasper & Clore, 1998; Peters & Slovic, 2000). There have been extensive attempts to study how evaluation of risk tolerance is influenced by demographic factors (see Grable (2008) and Cooper et al. (2014) for a comprehensive list). Thus, it is reasonable to hypothesize that it is possible to utilize demographic characteristics of the investors to describe different levels of *AE*.

1.4 Research Problem

The literature clearly shows that some people make estimation errors (i.e., *RTEE*) when assessing their risk tolerance (Grable & Rabbani, 2014; Hallahan et al., 2004; Moreschi, 2005). However, there is little meaningful interpretation of *RTEE* in the literature. There is also a gap in understanding investors and their investment behavior in the context of affect (i.e., feelings) in risk tolerance.

The first research problem is to determine whether *RTEE* that exists in practice when risk attitudes are measured using a *FRT* questionnaire can be used as an indicator of *AE*. The literature shows that people tend to make estimation errors when assessing their risk tolerance. Several researchers (e.g., Gilliam, Chatterjee, & Zhu, 2010b; Gilliam & Grable, 2010; Grable & Rabbani, 2014; Grable & Roszkowski, 2007; Grable et al., 2009a; Lucarelli, Uberti, & Brighetti, 2014; Moreschi, 2005; Wong, 2011) reported the presence of *RTEE* in the datasets they used for their research questions. They considered *RTEE* to be an overestimation or underestimation of *FRT*. For measuring *RTEE*, Moreschi (2005) used the FinaMetrica dataset (25 item scale) and Grable and Roszkowski (2007), Grable et al. (2009a), and Gilliam and Grable (2010) used questionnaire data from the *GL-FRT* survey (i.e., 13 item scale). Theoretically, RaF hypothesis and CTT may be helpful to determine if *RTEE* can be used as an indicator of *AE*. It is well understood from the RaF hypothesis that affect is a powerful force that can drive investors to make decisions with little regard for their financial capability. The affective component of risk tolerance can potentially have more influence over financial decisions than the objective financial ability component. Regarding the gender difference in risk tolerance, Loewenstein et al. (2001) argued that this difference might be because females report more and better imagery than males and they experience affect (i.e., feelings) more intensely than males, on average. There is also a possibility that emotional changes associated with aging may help to explain observed age-based differences in risk taking (Grable et al., 2009a). The evidence supports the argument that *SE* of risk is comprised of *OE* and *AE*, as well as systematic error. Thus, if *OE* and *SE* are known, then it may be possible to estimate *AE*. Moreover, the CTT framework is useful in showing that *RTEE* may serve as a proxy for *AE*. Regression analysis can be used to estimate the part of *SE* that can be explained by *OE*. Therefore, the remainder part of *SE*, which is basically *RTEE*, can be considered as an *AE* indicator.

The second research problem is whether it is possible to use demographic variables to describe investors who show similar affect (i.e. *AE*). The current literature suggests that based on estimation errors made by investors make while assessing their subjective risk tolerance, people can be classified into one of three groups: (a) overestimating, (b) underestimating, and (c) accurately estimating (Hallahan et al., 2004; Moreschi, 2005). These are very broad categorizations, where traditionally the extent of deviation is not considered significant. A positive (+) value indicates an overestimation. A negative (-) value suggests an underestimation. As such, it is possible for a person with +3 and +1 to be placed in the same category of overestimation. A positive value may be regarded as a positive affect or a quality of goodness, and a negative value may be regarded as a negative affect. In this classification process, both individuals are assumed to be similar. In reality, the degree of overestimation or underestimation may also be an important issue that needs to be explored. Moreover, simple groupings limit further description regarding demographic characteristics that may be associated with the evaluation of *FRT*. For example, Grable et al. (2008) reported that being male is positively related to risk tolerance. Gilliam et al. (2010b) found that men are more likely to have higher risk tolerance than women. It is reasonable to assume that these and other demographic variables are also likely to be associated with estimation error of *FRT*. Therefore, demographic characteristics should provide a useful description of investors' *AE*.

1.5 Significance

Accurately describing someone's personal risk-tolerance is an important aspect of financial planning. Hanna et al. (2008, p.96), in their *FRT* review argued, "Assessment of risk-tolerance is fundamental to proper asset allocation within a household portfolio." Accurate assessment allows an individual, or his or her financial planner, to build a portfolio that is the most suited to help them reach future goals while enabling them to invest within their comfort zone. Much of the research on *FRT* has relied on an expected utility based approach (Hanna et al.). The current study utilizes a behavioral finance approach to financial risk-tolerance research in an effort to estimate affect or feelings associated with *FRT*.

Some individuals can forecast their risk tolerance better than others (Hallahan et al., 2004; Moreschi, 2005). As a financial planner attempts to advise a client about risk and risk tolerance, it is entirely possible that certain clients may comprehend the concept more readily than others. Even so, they are likely to make an estimation error when assessing their willingness to take risks due to their *AE*.

In the past twenty years, numerous studies have attempted to identify the demographic factors that are associated with risk tolerance (Grable, 2008). A variety of socio-economic variables has been proposed and tested. Research to date, however, has not always provided a consensus regarding the effect of these factors on risk tolerance (Sweet, 2013). This study tests if there is any pattern in *RTEE* as far as some key demographic variables are concerned.

In summary, the financial professional body of knowledge is evolving. Cumbie (2003) called for researchers to incorporate a number of topics, for example, strategic thinking, the concept of risk, and emotional intelligence into their work. This study addresses each of these concepts.

1.6 Need for the Study

Affect is an important element in shaping decision making; however, affect, emotions, and feelings are not easily evaluated using purely objective assessments. Almost all of the risk-tolerance measures available today require some objective evaluation of risk situations. Relying solely on objective assessment is likely to provide an inaccurate understanding of a client's risk tolerance. Moreover, Hallahan et al. (2004) and Moreschi (2005) demonstrated that there is a difference between an objective and a subjective risk-tolerance score (i.e., *RTEE*). In order to understand the affective influence on risk tolerance, the first step is to be able to estimate affect. For estimation of affect, *RTEE* appear to be a viable source because overestimation and underestimation of risk tolerance may indicate the contribution of affective processes associated with risk-tolerance estimation.

To a large degree, the current work is an exploratory one, taking place in the context of discovery. The previous literature shows that investors do make errors when estimating their *FRT*. It has also been reported that while both men and women exhibit estimation errors, men are more likely to overestimate. Barber and Odean (2001) found that males trade 45% more actively than females. There are other demographic characteristics that also explain estimation errors. As theoretical understanding of affective process and its impact on decision making is becoming more available, financial planning practitioners need tools that help them to quantify client feelings (i.e., affect) to better understand how subjective factors influence their clients investment decision. The current literature does not adequately provide a useful tool to assess investors' affect associated with *FRT*. This study develops a tool for researchers and practitioners to quantify affect, or feelings associated with *FRT*.

This study primarily attempts to quantify *AE* as a component of financial risk appraisal using estimation errors. The study describes demographic characteristics of different groups of investors based on their *AE*. The study uses these *AE* groups as explanatory variables to describe portfolio risk (*PR*) scores.

1.7 Research Questions

This study attempted to quantify affect (i.e., feelings) within the context of RaF hypothesis and CTT. Additionally, this study divided individual investors into different groups based on *AE*. The study further looked at the differences in demographic characteristics of *AE* groups. The final aim was to examine the association between *AE* and *PR* scores. This study attempted to answer the following specific research questions:

(1) Can items be identified that measure objective risk-tolerance reliably as a proxy for *OE*?

(2) Can items be identified that measure subjective risk-tolerance reliably as a proxy for *SE*?

(3) Can *SE* and *OE* be used to derive an estimation of affect (*AE*)?

(4) Can groups of *AE* be described based on investors' demographic characteristics?

(5) Is there an association among *AE* categories and investors' behavior, such as, *PR* scores?

1.8 Research Objectives

The primary goal of this research is to obtain more insight into *FRT* by analyzing how feelings are associated with *FRT* estimation. In order to achieve this goal, this study is subdivided into four related research objectives.

The first objective is to determine which items can be used to measure *OE* and *SE*. Researchers have used *SE* and *OE* to estimate *RTEE* (Hallahan et al., 2004; Moreschi, 2005). In this study, *RTEE* is measured as a deviation of a respondent's subjectively assessed *FRT* from scores from items a reliable and valid risk-tolerance scale.

The second objective is to design a method capable of quantifying *AE* within the framework of the RaF hypothesis. The current literature does not provide a useful tool for measuring affect in *FRT*. The RaF hypothesis, along with CTT, can be used conceptually to quantify *AE* using *RTEE*. The RaF hypothesis suggests that feelings associated with risk may be measured using *AE,* while CTT suggests that *AE* may be indicated by the error related to measuring risk-tolerance (i.e., *RTEE*).

The third objective is to use demographic characteristics to describe each *AE* group. Previous research has found that gender, age, marital status, income, and education are related to estimation errors in *FRT*. However, these findings are not conclusive. The study advances the literature by showing how well these variables describe *AE*.

The fourth objective of the study is to use the *AE* groups to test how *PR* score is associated with *AE* groups. It is well documented that investors allow their feelings to influence their investment decisions. This study provides details about whether *RTEE* is associated with investing behavior.

1.9 Definitions

1.9.1 Financial risk tolerance. In this study, financial risk tolerance (*FRT*) is defined as the maximum amount of risk or uncertainty an individual is willing to accept when making a financial decision (Grable et al., 2008). This definition has its origin in Irwin's (1993) writings. He defined risk tolerance as the willingness to engage in behaviors in which the outcomes remain uncertain with possibility of an identifiable adverse outcome.

1.9.2 Grable and Lytton *FRT* scale. The Grable and Lytton risk-tolerance (*GL-FRT*) scale is a 13-item (Appendix A) financial risk-tolerance scale that, according to Grable and Lytton (1999), represents (a) investment risk, (b) risk comfort and experience, and (c) speculative risk.

1.9.3 Financial risk-tolerance estimation error. Financial risk-tolerance estimation error (*RTEE*) is defined as the deviation of a respondent's subjectively assessed *FRT* from scores on a reliable and valid risk-tolerance scale. Grable and Roszkowski (2007) defined *RTEE* as the systematic overestimation or underestimation of a person's *FRT* compared to an independent criterion. People are thought to either overestimate or underestimate or accurately estimate their risk-tolerance.

1.9.4 Objective evaluation of risk tolerance. Objective evaluation of risk-tolerance (*OE*) is defined as an investor's calculated risk-tolerance score using a psychometrically valid risk-tolerance assessment questionnaire. In this study, it is shown that a modified *GL-FRT* scale (based on cognitive assessment items in Appendix A) can be used as a proxy for objective risk-tolerance scores. *OE* is thought to rely primarily on a person's "analytic system" that uses algorithms and normative rules, such as probability calculus, formal logic, and risk assessment. In the literature, the analytic system is also interchangeably used with the term cognitive evaluation.

1.9.5 Subjective evaluation of risk tolerance. Subjective evaluation of risk tolerance (*SE*) is an investor's willingness to take financial risk that is assessed subjectively. *SE* can be measured using answers to the following question: "In general, how would your best friend describe you as a risk taker? The responses include: (a) a real gambler, (b) willing to take risks after completing adequate research, (c) cautious, and (d) a real risk avoider. This is the first item on the Grable and Lytton Risk-Tolerance Scale (Appendix A).

1.9.6 Affective evaluation of risk tolerance. Affective evaluation of risk tolerance (*AE*) is the difference between an investor's *SE* and their predicted *SE* using an *OE*. *AE* is thought to be an indicator of a person's intuitive, fast, mostly automatic, and not very accessible to conscious awareness calculation when making risk calculations (Slovic et al., 2004). This is also known as the "experiential system."

1.9.7 Affect. Affect means the specific quality of goodness or badness (a) experienced as a feeling state (with or without consciousness) and (b) demarcating a positive or negative quality of a stimulus (Slovic et al., 2004). The terms affect and feelings are used interchangeably in this study.

1.9.8 Portfolio Risk (*PR*). It is a score calculated by multiplying the riskiness weights for each investment asset class by the percentage of the individual's assets invested in that class, and summing over classes. A similar measure was used by Corter and Chen (2006) and Morse (1998) to score individual's portfolio risk. This study used weights as suggested by Corter and Chen: (a) cash (0.0), (b) fixed (0.12), (c) equities (0.2), and (d) other (0.12).

1.10 Limitations, Assumptions, and Delimitations

1.10.1 Limitations. This study is limited by the fact that *AE* related to *FRT* is not measured directly; rather, it is estimated from estimation errors. The outcome variable used in this study includes questions that may reflect the *AE* of financial risk. It is further acknowledged that this study is limited to the evaluation of *FRT*. Application of this research to other domains of risk is not presumed. The researcher acknowledges that no attempt was made to test all of the demographic factors that can be used to classify individuals into investor profile groups. This study relies on a secondary data set; thus, analysis is limited to variables available in the dataset. All responses are self-reported; thus, these may be prone to response bias.

1.10.2 Assumptions. This study assumes that financial *RTEE* represents *AE*. The following specific research assumptions were made regarding the online data collection process: (a) respondents answered all relevant questions truthfully, to the best of their ability, without influence from others; (b) participants did not attempt to complete multiple questionnaires in the same period; and (c) the risk scale used was psychometrically robust, and as such, a reasonably accurate measure of *FRT*.

1.10.3 Delimitations. Delimitations are choices the researcher makes in order to limit the scope of the study. In this study, the researcher was not able to control the sample selection; thus, respondents may not represent a valid random sample. The focus of this research is on investors and their behavior. However, the dataset contains respondents who did not have any assets for investment. The study was delimited to exclude those respondents who did not have investable assets. In addition, the study was delimited to exclude younger respondents as the previous literature reported that respondents below 35years of age are generally less likely to have retirement accounts than those above 34 years (Glumov, 2013).

1.11 Summary

Financial planners are responsible for understanding individual attitudinal differences to determine the appropriate portfolio for their clients. In determining an optimal portfolio allocation, determination of *FRT* is fundamental. The problem is that it is common for an investor to make errors when assessing his/her *FRT*. This chapter has provided an overview of *AE* as it relates to *FRT* and risk-tolerance estimation errors (*RTEE*). The Risk-as-Feelings (RaF) hypothesis was presented, and an explanation of a conceptual framework to estimate affect or feelings was provided. A brief review of the literature indicated that *RTEE* can be used as an indicator of *AE*. The purpose, justification, and particular research question to be answered were offered. The information provided in this chapter gives an explanation for the necessity of research into how financial planners can estimate affect or feelings and use it to understand how it influences portfolio allocation. As discussed, the research questions require a series of exploratory and confirmatory data analyses. An introduction to how variables of affect, age, gender, marital status, education, and household income were associated with investors' behavior was presented. . The chapter concluded with definitions, limitations, assumptions, and delimitations. The remainder of this thesis is organized as follows: (a) Literature Review; (b) Methodology; (c) Results; and (d) Interpretation, Conclusion, and Recommendation.

CHAPTER 2

REVIEW OF LITERATURE

2.1 Historical Context

There is a long history associated with the measurement and assessment of risk and risk tolerance. This history goes hand in hand with the academic development of mathematics. Before the Renaissance, people perceived the future as a matter of luck or the result of random variations; society was not prepared to attach numbers to risk, and most consumer decisions were driven by instinct (Bernstein, 1998). During the Renaissance, Blaise Pascal and Pierre de Fermat articulated the fundamental laws of probability, which Bernstein (1998) called the mathematical heart of the concept of risk.

Daniel Bernoulli, in 1738, authored *Specimen Theoriae Novae de Mensura Sortis* (Exposition of a New Theory on the Measurement of Risk), which provided the dominant paradigm of economic theory of risk aversion, risk premium, and marginal utility that has been used for 250 years. Bernoulli found that as individuals increase their wealth, they require greater guaranteed returns in order to risk more money, and in general, people tend to prefer less risk to more. This was the standard risk paradigm through the early 20th century. The next breakthrough in risk research came from Von Neumann and Morgenstern (1947) and Friedman and Savage (1948) who challenged the standard utility function assumption by showing that most people do not exhibit constant risk aversion throughout the entire domain of wealth. They postulated a utility function with both risk-taking and risk-avoiding segments.

The earliest works on the measurement of risk attitude focused primarily on consumer behavior. Post-World War II works dealt with risk in other fields, such as finance (Cohn, Wilbur, Lease, & Schlarbaum, 1975; Markowitz, 1952; Siegel & Hoban, 1982), business (Fitzpatrick, 1983), natural hazards (Kunreuther, 1979), and physical situations (Newman, 1972; Slovic, Fischhoff, & Lichtenstein, 1978). One of the key developments during this time was the emergence of Modern Portfolio Theory (MPT) as articulated by Markowitz (1952). This paradigm shows that risk-averse investors can construct portfolios to optimize or maximize expected return based on a given level of market risk. Diversification is the key to this optimization. According to Bernstein (1998), MPT "touched the intellectual movement that revolutionized Wall Street, corporate finance, and business decisions around the world; its effect is still being felt today" (p. 6).

Another advancement in the study of risk attitudes came from Wallach and Kogan (1961) who used Choice Dilemmas Questionnaires to measure risk-tolerance in everyday life situations. With these questionnaires, subjects were asked to advise other individuals regarding 12 choices with two outcomes that had a sure gain or sure loss. Until the mid-1970s, choice dilemma questionnaires were commonly used to measure risk-taking propensities. There are different forms of the choice dilemma instrument, such as dot estimation tests, word meanings tests for category width, life experiences inventories, multiple choice exams, recreational activity measures, job preference inventories, gambling assessments, and peer ratings. However, the choice dilemma instrument approach was criticized for lack of validity and reliability. Slovic (1962) reported lack of consistency between and among questionnaires. MacCrimmon and Wehrung (1985) and Slovic concluded that low validity was due to the use of one-dimensional questions (e.g., how risk tolerant are you?). MacCrimmon and Wehrung also concluded that, “There is no particular reason to believe that a person who takes risks in one area of life is necessarily willing to take risks in all areas” (p. 51).

Further development of risk-assessment methods shed doubt on economists’ claims that risk-taking propensities and preferences could be represented and understood within a utility function environment (Bell, 1982; Kahneman & Tversky, 1979; Loomes & Sugden, 1982; Payne, Laughhunn, & Crum, 1984; Shefrin & Statman, 1993; Tversky & Kahneman, 1981). In their prospect theory paradigm, Kahneman and Tversky (1979) found that people are more willing to take risks when certain losses are anticipated than when certain gains are anticipated. Consequently, Kahneman and Tversky concluded that individuals, in general, exhibit risk-taking preferences for losses and risk avoidance preferences for gains. Therefore, it has since been concluded that the use of choice dilemmas and utility function modeling, as procedures to measure risk-tolerance, sometimes lead to inadequate and inaccurate assessments.

The limitations of both classical economic theory and behavioral studies are outlined by a third stream of studies. Amongst others, Loewenstein et al. (2001) observed that virtually all current theories of choice under risk or uncertainty are cognitive and consequentialist. A consequentialist perspective means making decisions based on the assessment of the consequences of possible choice alternatives (see Section 2.6 for more details). These frameworks assume that people assess the desirability and likelihood of possible outcomes of choice alternatives and integrate this information into some expectation-based calculus to arrive at a decision. Loewenstein et al. proposed an inclusive theoretical perspective, namely, a Risk-as-Feelings (RaF) hypothesis, resulting from a range of clinical and physiological studies. They provided evidence that emotional reactions to risky situations often diverge from an individual’s cognitive assessments. This new stream of studies relied on the concept that emotions often overcome rationality when making decisions under uncertainty (Dillard et al., 2012; Galentino & Bonini, 2014; Loewenstein, 2000; Peters & Slovic 2000; Wang et al., 2014).

2.2 The Concept of Risk

The word ‘risk’ derives from the early Italian *risicare*, which means ‘to dare.' “The actions individuals dare to take, which depends on how free they are to make choices, are what the story of risk is all about” (Bernstein, 1998, p. 8). In this sense, the decision to engage in a risky behavior is a choice rather than fate. As simple as it sounds, there is a great deal of ambiguity in defining risk.

The concept of risk in economics ranges from normative to positive. MacCrimmon and Wehrung (1985) defined risk in the context of their research as, “The exposure to the chance of loss” (p. 52). In their definition, the degree of risk is determined by lack of control, lack of information, and lack of time. Schooley and Worden (1996) conceptualized risk as the probability of losses. Dembo and Freeman (1998) defined risk as, “A measure of the potential changes in value that will be experienced in a portfolio as a result of changes in the environment between now and some future point in time” (p. 35). Shapira (1995) considered risk as a context dependent concept and argued that it needs to be studied in natural settings associated with decision making. Bernstein (1998) highlighted the evolution of risk from normative economics, mathematics, and statistics to behavioral finance. He noted that risk has several meanings and that each individual has specific ideas about the concept of risk (Fisher & Statman, 1999). In most financial literature, the terms risk and uncertainty are used interchangeably (Reilly & Brown, 2000).

2.3 The Concept of Financial Risk

One of the more concrete and universally agreed measures of financial risk was proposed by Markowitz (1952) in the context of MPT. He used variance and standard deviation of return as a measure of risk. With the introduction of the CAPM, beta became another metric for the measurement of risk, particularly systematic risk (Sharpe, 1964).

Some authors, such as Bodie (1994), Thorley (1995), Schooley and Worden (1996), and Olsen and Khaki (1998), view financial risk as the failure to reach some specified target rate of return. For example, Schooley and Worden described financial risk as the possibility that the expected return on an investment will not occur and that the value of the security will fall. The U.S. Securities and Exchange Commission's definition of risk also shares this view: "All investments involve some degree of risk. In finance, risk refers to the degree of uncertainty and/or potential financial loss inherent in an investment decision. In general, as investment risks rise, investors seek higher returns to compensate themselves for taking such risks" (SEC, 2014).

Among different risks, financial risk has similarities to the general definition of risk; however, it is unique in its purpose and context. In summary, financial risk tends to be measured by standard deviation and beta. Financial risk reflects uncertainty in terms of expectations.

2.4 The Concept of Financial Risk Tolerance

Financial risk tolerance (*FRT*), which is defined as the maximum amount of risk or uncertainty an individual is willing to accept when making a financial decision (Grable et al., 2008), plays a central role in financial planning. If the assessment of risk-tolerance is accurate, it can be assumed that financial decisions taken under uncertainty are more likely to be optimal.

However, there are disagreements among researchers and practitioners on the degree of accuracy of the many risk-tolerance assessment tools available. Many of these tools are psychometrically valid and reliable; however, often they fail to deliver optimum outputs when making financial decisions.

Many definitions of *FRT* available in the literature are context dependent and can be viewed from multiple perspectives, such as regulatory, financial, behavioral, and operational. Normatively, an investor’s *FRT* is reflected by the concept of risk aversion. Many economists mathematically define *FRT* as the reciprocal of risk aversion (Barsky, Juster, Kimball, & Shapiro, 1997; Gron & Winton, 2001; Walls & Dyer, 1996). A consumer’s expected utility function is typically assumed to resemble a constant relative risk aversion utility function (Hanna, Gutter, & Fan, 2001). Constant relative risk aversion is represented graphically so that as wealth increases, marginal utility slowly increases but at an ever slowing rate. Low *FRT* is represented by a concave utility function, whereas a convex utility function is representative of high *FRT*. An investor is risk averse if she always prefers a sure wealth level to a lottery. If she prefers a lottery to the sure outcome, she is deemed to be a risk seeking individual. If an investor is indifferent, she is a risk neutral individual. However, MPT assumes a straightforward concept of risk-tolerance; namely, investors are risk averse. Therefore, when the level of risk aversion is identified, investors should be able to select their preferred allocation from a number of efficient portfolios. In financial planning practice, advisors try to gather data regarding an investor’s attitude toward financial uncertainty by assessing risk-tolerance. The purpose of this process is to determine the asset allocation that provides the highest level of return for a given level of risk.

Harlow and Brown (1990) defined *FRT* as, “The degree to which an investor is willing to accept the possibility of an uncertain outcome to an economic decision” (p. 51). Callan and Johnson (2002) defined *FRT* as, “The degree to which a client is willing and able to accept the possibility of uncertain outcomes being associated with their financial decisions” (p. 32). *FRT* represents the extent to which an investor is willing to risk experiencing a less favorable financial outcome in the pursuit of a more favorable financial outcome (International Organization for Standardization, 2006). As noted previously, *FRT* is defined in this study as the maximum amount of risk or uncertainty an individual is willing to accept when making a financial decision (Grable et al., 2008). What is common to each definition is the idea of “willingness to accept” an uncertain outcome. The first three definitions do not specify the level of “degree”, whereas Grable et al. (2008) regarded “degree” at the maximum level. Due to the precise nature of the definition, this study uses the definition of Grable and his associates.

2.5 Regulatory Environment Relating to Risk-Tolerance Assessment

Financial services regulators, both domestically in the United States and internationally, consider *FRT* as a critical element of quality investment advice. FINRA Rule 2111 (Suitability) requires that a firm or associated person “have a reasonable basis to believe that a recommended transaction or investment strategy involving a security or securities is suitable for the customer, based on the information obtained through the reasonable diligence of the member or associated person to ascertain the customer’s investment profile.” In Regulatory Notice 12-25, FINRA provided additional guidance on the issue of suitability. FINRA categorically stated, “A broker must have a reasonable basis to believe that an . . . investment strategy . . . is suitable for a particular customer based on the customer’s investment profile and the new rule broadens the explicit list of customer-specific factors that firms . . . must attempt to obtain and analyze when making recommendations to customers. The new rule adds a customer's . . . risk tolerance to the explicit list of customer-specific factors . . ." For the purpose of the suitability rule, FINRA defined "Risk Tolerance" in Regulatory Notice 11-25 as, "A customer's ability and willingness to lose some or all of [the] original investment in exchange for greater potential returns."

The U.S. federal government does not provide guaranteed protection for securities, as it does for savings deposits, insured money market accounts, or certificate of deposits through the Federal Deposit Insurance Corporation (FDIC) and the National Credit Union Administration (NCUA). Securities an investor owns, including mutual funds that are held by a broker or a bank's brokerage subsidiary, are not insured against loss in value. The Securities Investors Protection Corporation (SIPC), a non-government entity, replaces missing stocks and other securities in customer accounts held by SIPC member firms up to $500,000, including up to $250,000 in cash, if the firm fails (SEC, 2014), but not due to securities losses. Because of this, it is important for financial advisors to match each client's risk tolerance to an appropriate asset allocation framework as a way to account for a client's comfort level associated with potential losses.

In Europe, the Markets in Financial Instruments Directive (MiFID), which was effective from November 2007, requires European financial services providers to categorize investors and their suitability for each type of investment product. Financial service professionals in the European Union are now required to have a 'reasonable basis' to provide investment advice on a specific product. In Australia, the Financial Services Reform Act (FSRA) 2001 requires that all financial advice on asset allocation and portfolio selection (investment products) must conform to ‘reasonable basis.’ A ‘reasonable basis’ of advice is essentially related to each client’s tolerance of risk. In Canada, the Rule 1300 of the Dealer Member Rules of the Investment Industry Regulatory Organization of Canada (IIROC) requires that financial advisors must meet the requirements of the “Know Your Client” (KYC) rule to ensure their advice is suitable for their clients in terms of their financial situation, investment knowledge, investment objectives and risk tolerance.

Although these regulatory frameworks stress the importance of risk-tolerance assessment as a means for providing quality investment advice, assessment of risk tolerance is left to individual financial advisors and firms. As a result, by assessing risk tolerance using currently available tools, some advisors and firms may be merely fulfilling regulatory compliance obligations. The effectiveness of these assessments may not be given adequate importance.

2.6 RaF Hypothesis as a Conceptual Framework

Many scholars from different disciplines have analyzed how risk, risk perception, and risk tolerance influence individuals when making choices under uncertainty. The notion of risk in the decision-making process is an essential element when evaluated from a classical economic theoretical framework (i.e., the so-called normative approach) that ranges from the EUT perspective of Von Neumann and Morgenstern (1947) to MPT of Markowitz (1952). However, in stark contrast, the early works of behavioral economics in the 1970’s, such as prospect theory (Kahneman & Tversky, 1979) up to the more recent Behavioral Portfolio Theory (Shefrin & Statman, 2000), have introduced evidence of cognitive biases that alter rational decision making.

Loewenstein et al. (2001) observed that virtually all current theories of choice under risk or uncertainty are cognitive and consequentialist. In traditional models, the decision-maker is assumed to assess the consequences of possible choice alternatives quantitatively and choose the outcome that has the best risk-benefit trade-off. For example, MPT and CAPM, the two most influential expected utility based theories, are based on the consequential model of decision-making process. As illustrated in Figure 2.1, the consequentialist model of decision-making posits that risky choice can be predicted by assuming that people assess the severity (anticipated outcomes) and likelihood (probability) of outcomes of choice alternatives, and integrate this information cognitively to arrive at a decision. Loewenstein et al. observed that feelings triggered by the decision situation is not integral to this decision-making process. Thus, the consequentialist perspective assumes that risky decision making is a cognitive activity and that feelings are an outcome of cognitive processes not integral to the decision making process.

However, there is ample evidence that feelings have a significant influence on decision-making. For example, Holtgrave and Weber (1993) showed that affective reactions play a crucial role even in seemingly “objective” contexts such as financial investment decisions. Damasio (1994) showed that the quality of decision making suffers when feelings (affective inputs) are suppressed by having decision makers think cognitively about the pros and cons of a decision. Alhakami and Slovic (1994) found that the inverse relationship between perceived risk and perceived benefit of an activity was linked to the strength of positive or negative affect associated with that activity. Finucane et al. (2000) found that information stating that the benefit is high for a technology, such as nuclear power, would lead to more positive overall affect that would decrease the perceived risk. Ganzach (2001) noted that analysts base their judgments of risk and return for unfamiliar stocks upon a global attitude.

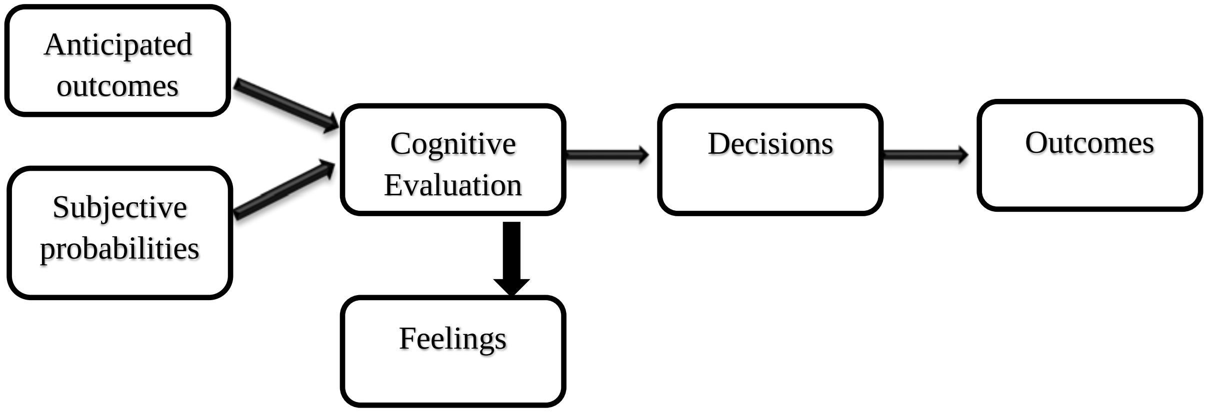

Figure 2.1. Consequentialist perspective of risk (Loewenstein et al., 2001).

The inherent weakness of the consequentialist perspective and recent developments in neuroscience led Loewenstein et al. (2001) to propose a further theoretical perspective, namely, the RaF hypothesis. The RaF hypothesis is based on a range of clinical and physiological studies. Loewenstein et al. provided evidence that a decision maker evaluates a risky situation in two ways: cognitively and affectively. RaF hypothesis studies rely on a concept that has now become an accepted axiom: emotions often overcome rationality when making decisions under uncertainty (Damasio, 1994; Loewenstein, 2000; Peters & Slovic, 2000). At a minimum, the literature shows that emotions supplement cognitive appraisals (Dillard et al., 2012; Galentino & Bonini, 2014; Loewenstein, 2000; Peters & Slovic, 2000; Wang et al., 2014).

Modern psychological theories suggest that there are two fundamentally different ways in which humans make decisions. One is an affective system that is evolutionarily older, fast, and mostly automatic (Slovic & Weber, 2002). This system is based on an association/similarity system. The other one is cognitive that works by algorithms and rules. This system is slower, effortful, and requires awareness and conscious control. Slovic and Weber (2002) observed that cognitive and affective systems often work in parallel. The affective system is intuitive, automatic, and fast, which is the most natural and most common way to respond to a threat (Slovic et al., 2004). This system transforms uncertain and threatening aspects of the environment into affective responses (e.g., fear, dread, anxiety) and thus represents risk as a feeling (Loewenstein et al., 2001).

Loewenstein et al. (2001) suggested that people assess the desirability and likelihood of possible outcomes of choice alternatives and integrate this information into some expectation-based calculus to arrive at a decision. In an ideal world, calculus matches the actual risk environment; however, this is rarely the case. The vast majority of investors either overestimate or underestimate risk in a given situation (Hallahan et al., 2004; Moreschi, 2005).

The RaF hypothesis model was developed primarily to incorporate the fact that the emotions people experience at the time of making a decision influence their eventual behavior. As shown in Figure 2.2, three premises to support the argument that decision making involving risk and uncertainty is influenced by feelings are:

(a) Cognitive evaluations induce emotional reactions. This argument is well established by psychologists (Loewenstein et al., 2001).

(b) Emotions inform cognitive evaluations. The idea that emotions inform cognitive evaluations is also well established in the psychology and decision making literature. Research shows that people in positive moods tend to make optimistic judgments, while people in negative moods tend to make pessimistic judgments (Loewenstein et al., 2001).

(c) Feelings can influence behavior (i.e., decisions and behavioral outcomes). Damasio (1994) showed that emotions play a vital role in decision-making by studying people who had an impaired ability to experience emotion. Individuals with impaired ability to experience emotions had difficulty making decisions and tended to make suboptimal decisions.

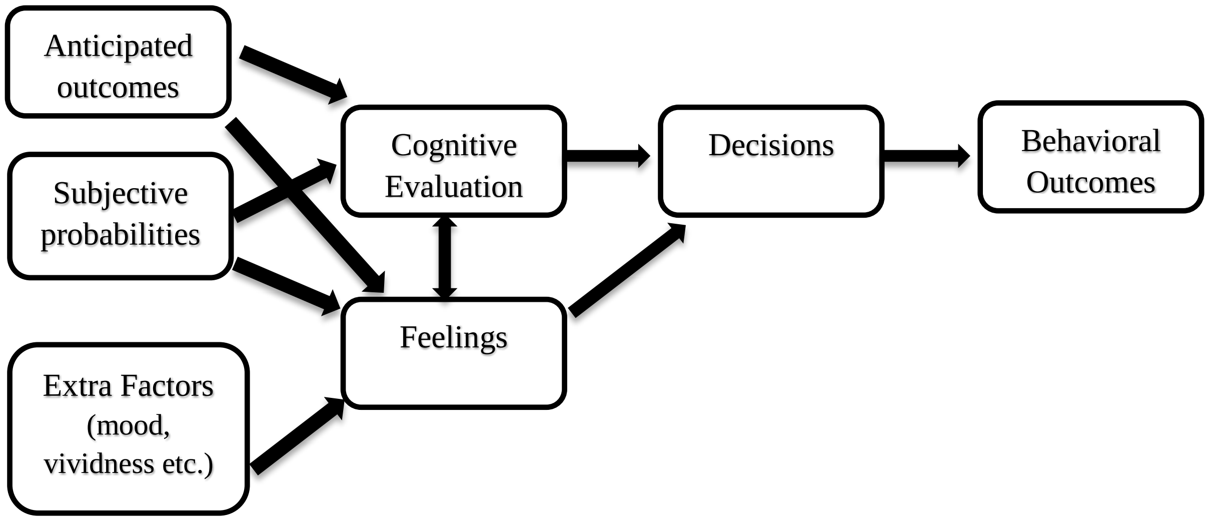

Figure 2.2. RaF hypothesis (Loewenstein et al., 2001).

The RaF hypothesis framework, as illustrated in Figure 2.2, explains a range of behaviors that demonstrate divergence between cognitive evaluations and feelings (e.g., failure to act in accordance with one's values, to comply with one's intentions and goals, or seemingly irrational behavior, such as specific phobias and various forms of affect-driven activities ranging from interpersonal relationships to appetitive/aversive motives in general). Loewenstein et al. (2001) argued that the RaF perspective is feelings-based, in opposition to virtually all other models aimed at describing and predicting human behavior as these are consequentialist in nature.

In cognitive consequentialist accounts of risk related perception and behavior, anticipated outcomes and subjective probabilities are two central inputs. However, emotions respond to these inputs in a fashion different from cognitive evaluation of riskiness (Loewenstein et al., 2001). Moreover, there are other variables that influence emotion but have little impact on cognitive evaluation. These factors include vividness or associations they evoke, mood, time between the decision, and the realization of the outcome of the decision (Loewenstein et al.).

Few behavioral models explicitly outline the behavioral output resulting from ambivalence due to conflicting information from the two systems for information acquisition (Loewenstein et al., 2001), but the RaF hypothesis is an exception. The RaF hypothesis perspective has been incorporated into models that predict action selection in psychological risk-return models (Weber & Milliman, 1997). Apart from showing the high potential for disagreement between feelings and cognitive evaluations, the RaF hypothesis model suggests that, when such a tension arises, behavior tends to be driven by anticipatory feelings, (e.g., feelings experienced at the moment of decision making). By integrating outcome-related factors, such as anticipated outcomes, including anticipated emotions, the model incorporates several of the variables typically accounted for by the intentional/analytical system. The model includes empirical evidence showing that the affective/intuitive system may overrule cognitive evaluations when these are in conflict. "The risk-as-feelings framework is unique in terms of acknowledging the influences of cognitive and emotional factors on risk tolerance and risk-taking behaviors. The risk-as-feelings hypothesis offers a fresh approach to understanding both risk tolerance and risk-taking behaviors" (Grable, 2008, p. 8).

2.7 Use of Feelings in Risk Research

In the literature, reliance on feelings for decision making has been characterized as "the affect heuristic." Slovic et al. (2004) found support for the argument that rationality is not only the product of the analytic mind, but of the experiential mind as well. The authors traced the development of this heuristic across a variety of research paths and discussed some of the important practical implications resulting from ways that this heuristic impacts how people perceive and evaluate risk. They concluded that risk analysis can be benefited from experiential thinking. They also argued that risk analysis needs to be sensitive to feelings such as dread, equity, controllability, and similar factors that drive people's concerns about risk.

Lucey and Dowling (2005) investigated whether variations in feelings that are widely experienced by people influence investor decision making and, consequently, lead to predictable patterns in equity pricing. They showed that investors can sometimes invest in an equity based on whether they like or dislike a company. This is true even if the investment does not make sense mathematically.

Kobbeltvedt and Wolff (2009) conducted two empirical studies that tested the predictive power of consequence-based versus affect-based evaluative judgements for behavioral intentions. They noted that the Theory of Planned Behavior (Ajzen, 1991) is a model aimed at predicting planned- and goal-directed behavior using a consequentialist perspective, whereas the RaF hypothesis (Loewenstein et al., 2001) focuses on situations where risk-as-feelings is a crucial element. Kobbeltvedt and Wolff noted that there are conflicts between cognitive evaluations and anticipatory feelings, and where behavior cannot be understood from a pure consequentialist perspective, incorporating feelings into an analysis appears to add predictive power.

Lucarelli and Brighetti (2011) compared (a) an unbiased risk-tolerance score, obtained from psycho physiological reactions of individuals taking risk in a laboratory; (b) a biased risk-tolerance score obtained through a psychometrically validated questionnaire; and (c) actual financial choices made in real life. They reported that unbiased risk-tolerance score was much higher than the risk assumed in real life, but higher than the biased risk-tolerance score.

In an experimental study, Van Winden, Krawczyk, and Hopfensitz (2010) had participants put their own money at stake in a real investment task. Van Winden et al. explicitly measured affect. They conclude that feelings play a role in shaping investment decisions. Their results suggest that both positive and negative anticipated emotions should be taken into account while making a decision under risk.

Brighetti, Lucarelli, and Marinelli (2012) investigated whether there is any relationship between individuals' emotional profile and their insurance decision making. They explored how an emotional reaction in a condition of ambiguity and the fear of the unknown influence insurance choices. They found that these emotional variables increased the predictive power of models for insurance demand.

Weber, Weber, and Nosić (2012) surveyed UK online-brokerage customers and reported evidence that was consistent with the RaF hypothesis. They reported that changes in risk taking were associated with changes in subjective expectations of market portfolio risk and returns, but less with changes in numeric expectations.

Bassi, Colacito, and Fulghieri (2013) tested the impact of sunshine and good weather on risk-taking behavior. They found that weather may affect individual risk tolerance through its effect on mood. They provided evidence that weather can induce positive affect. They also provided a framework for assessing the impact of positive affect on willingness to take risks in financial decisions. Conte, Levati, and Nardi (2013) used expected utility based models to investigate the impact of emotions on risk preferences. They found that participants in a joviality treatment were more risk-seeking than those in the control group.

Wang et al. (2014) used the RaF hypothesis to illustrate that when consumers panic this will influence their risk perception. They found that perceived probability was higher than objective probability. They also found that perceived probability was positively correlated with panic. Lucarelli et al. (2014) verified the RaF hypothesis in their empirical research on classifications in *FRT*. They noted evidence that emotions drive financial choices. In their study, they found that probability of misclassification was higher when financial risk-tolerance questionnaires were used compared to when emotional reactions were used.

Li, Sang, and Zhang (2015) investigated the relationship between an emotional regulation strategy and *FRT*. They found that emotion regulation was negatively related to financial risk tolerance. Taken together, these studies provide evidence that a strong link between feelings and risk-tolerance assessment is likely present.

2.8 Measurement of *FRT*

Nearly all previous analyses of risk tolerance have either implicitly or explicitly been based on the concept of risk aversion using an expected utility framework. For example, Sung and Hanna (1996) and Hanna and Chen (1997) used an expected utility approach to demonstrate that important aspects of objective risk tolerance are the proportion of an investor's total wealth (including human capital) held in financial assets and the investment horizon. Barsky et al. (1997) presented an experimental measure based on a set of hypothetical questions asked of a large national sample of adults aged 51 to 61. Their measurement linked the theoretical concept of relative risk aversion with a willingness to engage in an income gamble. The measurement used by Barsky et al. is theoretically sound, but it has at least three potential ambiguities (Hanna et al., 2001) about (a) tax, (b) level of risk aversion, and (c) types of alternatives. Hanna et al. (2001) used pension choice questions to measure risk aversion that include more risk aversion levels that also considered a permanent income drop. Later, Hanna and Lindamood (2005) added graphical illustrations to these pension choice questions.

Alternatively, there are a number of other ways researchers and practitioners may assess *FRT*. The most common methods include interviews, portfolio composition methods, and psychometric approaches. A *FRT* assessment instrument needs to include these five elements: "(1) some central concept of risk, (2) allowance for the derivation of a risk measure, (3) relevance to respondents, (4) ease of administration, and (5) adequate validity and reliability" (Grable & Lytton, 1999, p. 167). Roszkowski et al. (2005) reviewed academic and industry risk-tolerance questionnaires and noted that most risk-tolerance questionnaires fail to address validity and reliability issues adequately.

One commonly used risk-tolerance assessment item is the Federal Reserve Board's Survey of Consumer Finances (SFC) risk-tolerance question. The risk-tolerance question in the SCF has been measured in national surveys since 1983. This question is related to risk tolerance in terms of saving and making investments. Scores can be used to determine a respondent's *FRT* as highly risk tolerant, above-average risk tolerant, average risk tolerant, or not risk tolerant. The SCF item has traditionally been used as a measure of risk-tolerance, but Hanna et al. (2001) suggested that the SCF item does not have a reliable connection to economic theory. Grable and Lytton (2001) pointed out the SCF question has some weaknesses and does not adequately represent a wide spectrum of *FRT* attitudes.

Another risk-tolerance assessment instrument, the FinaMetrica Personal Financial Profiling system, has been scientifically and psychometrically validated for use in assessing *FRT* (Roszkowski et al., 2005). The FinaMetrica risk-tolerance questionnaire is comprised of 25 questions designed to measure a respondent's risk tolerance using a single standardized (0-100) Risk-Tolerance Score (RTS). A higher RTS indicates that the respondent can tolerate a higher level of financial risk; conversely, a lower RTS indicates risk aversion. The scale has a mean of

50 and a standard deviation of 10. The 0 to 100 range is divided into seven segments or risk-tolerance categories. Given the proprietary commercial origin of the scale, research using the tool has been limited.

There are several other financial risk-tolerance assessment instruments available in the market. For example, Pocket Risk, a web-based questionnaire, assesses an individual's *FRT*. There are a total of 20 questions. This instrument scores an individual's risk-tolerance relative to a sample of the U.S. population. Score can range from 0-100, with lower scores demonstrating low-risk qualities and higher scores demonstrating high-risk qualities. The Cronbach's alpha of this instrument is 0.82. Pocket Risk requires a user to supply a credit card to initiate a free trial. Another tool, Oxford Risk Rating, is currently available for business uses in the UK only. Grable and Lytton (1999) developed a measure that considers multiple dimensions of *FRT*. The instrument includes 13 questions that measure several aspects of risk, including (a) guaranteed versus probable gambles, (b) general risk choice, (c) choice between sure loss and sure gain, (d) risk as related to experience and knowledge, (e) risk as a level of comfort, (f) speculative risk, (g) prospect theory, and (h) investment risk (Table 2.1). The measure initially included 100 items. Through validity tests, item analysis, and factor analysis, the instrument was reduced to 13 questions. The 13-item measure examines the constructs of investment risk, risk comfort and experience, and speculative risk (Grable & Lytton, 1999). The 13-item *GL-FRT* scale has undergone reliability and validity tests and has been used in numerous research studies. Financial planning firms working with clients have also been using the 13-item measure. Scores on the test can range from 13 to 47. Higher scores are descriptive of increased *FRT*. As noted, there are multiple ways to evaluate *FRT*. The *GL-FRT* provides a good mix of validity, reliability, and open access for researchers.

Table 2.1

Description Items used in GL-FRT Scale

Item	Guaranteed vs Probable gambles	Choices between sure loss and sure gain	Risk as experience and knowledge	Risk as a level of comfort	Speculative risk	Prospect theory	Investment risk
1			X	X			
2	X				X		
3				X			
4			X				X
5			X	X			X
6			X	X			
7			X		X		X
8	X	X			X		
9						X	
10						X	
11			X				X
12				X		X	
13	X					X	

Source: Adapted from Grable and Lytton, 1999

2.9 Association of Demographic Factors with *FRT*

The association of demographic characteristics with *FRT* is one of the most widely investigated subjects in the financial planning literature. A number of studies have been conducted to examine how *FRT* is associated with demographic characteristics. The most commonly cited characteristics are age, gender, marital status, education, and income (Grable, 2008). There is a consensus among financial planners, investment managers, and researchers that demographic factors can be used to both differentiate among levels of investor risk tolerance and classify investors into risk-tolerance categories in terms of offering better-suited products and services to clients. This opinion, however, is not universally held. For example, Wong (2011) argued that a person's demographic standing does not have a big impact on shaping a person's level of risk-tolerance. Some sort of psychological or personality evaluation of a person's attitude toward risk may also be needed (Ardehali, Paradi, & Asmild, 2005). Table 2.2, from Cooper et al., (2014), summarizes the reported associations among some demographic variables and risk tolerance. These factors are described in more detail below.

Table 2.2

Relationship of Demographic Variables with Risk Tolerance

Demographic variable	Relationship with Risk Tolerance
Gender	Greater for men
Age	Inconclusive
Marital and family status	Inconclusive
Investor experience, financial knowledge and education	Increases with experience, education, knowledge of risk and personal finance
Income and wealth	Increases with income and wealth
Occupation	Greater for self-employed, higher ranked, professionals, and those in the private sector

Source: Cooper et al. (2014)

2.9.1 Gender. It has long been assumed that gender is significantly related to risk tolerance. Both anecdotal and empirical evidence suggest that women are more risk averse than men (Ahmad, Safwan, Ali, & Tasbasum, 2011; Al-Ajmi, 2008; Bajtelsmit & Bernasek 1996; Cohen & Einev, 2007; Faff, Mulino, & Chai, 2008, Gibson, Michayluk, & de Venter, 2013; Gilliam et al., 2010a; Gilliam et al., 2010b; Grable, 2000; Grable & Lytton, 1998; Neelakantan, 2010, Yao & Hanna, 2005; Wong, 2011). One possible reason for the difference is cultural

(Slovic, 1966). Another explanation is that women have higher levels of the enzyme monoamine oxidase that reduces sensation seeking (Hallahan et al., 2004). Roszkowski (1998), however, suggested that while historically men were more risk tolerant than women, this distinction is becoming less prevalent.

Bajtelsmit, Bernasek, and Jianakoplos (1999) used the 1989 SCF and studied gender differences in defined contribution plans. They concluded that holding everything else constant, women were less risk tolerant than men in portfolio allocation decisions in their defined contribution pension plans. Hariharan, Chapman, and Domian (2000) investigated the behavior of investors nearing retirement and found that women were more likely to invest in risk-free securities than men, which indicated that women were less risk tolerant than men. Further research has been reported that decreased risk tolerance is associated with the investment choices of women (Watson & McNaughton, 2007). Grable et al. (2008) employed structural equation modeling and factor analytic structural equations, using indicator and latent variables, to examine causal pathways leading to risk tolerance. Analyzing the results led these researchers to indicate that being male was positively related to risk tolerance. Agnew, Anderson, Gerlach, and Szykman (2008) conducted research using the lottery choice experiment created by Holt and Laury (2002). They concluded that not only were women significantly more risk averse than men, they were also less financially literate. More risk averse individuals also tend to be more conservative investors, which can lead to low levels of wealth accumulation (Neelakantan, 2010). If women are usually found to be more risk averse or less risk tolerant, this may account for the gender gap in wealth. Neelakantan (2010) observed that the difference in risk tolerance attributable to gender accounted for 10% of the gap in accumulated wealth. Based on

FinaMetrica data from three countries, Wong (2011) also reported that females tend to have lower risk tolerance than males.

Some studies have questioned the validity of claims that gender is useful in differentiating between levels of investor risk tolerance. These studies (e.g., Deaves, Veit, Bhandari, & Cheney, 2007; Embrey & Fox, 1997; Grable & Joo, 1999; Grable & Lytton, 1999; Harrison, Lau, & Ruström, 2007; Hanna, Gutter, & Fan, 1998; Ho, 2009; Sundén & Surette, 1998) have indicated that gender is not a significant determinant of *FRT*.

Schubert, Brown, Gysler, and Brachinger (1999), using questions either framed as investment or insurance decisions, or as abstract gambling decisions, found that males and females did not differ in their risk propensities toward contextual decisions, but gender differences in risk propensity did exist in abstract gambling decisions. They concluded that males and females do not have different stereotypic risk attitudes; gender-specific risk behavior found in previous research might be due to different opportunity sets that males and females faced.

Brighetti and Lucarelli (2013), using the IOWA Gambling Task (IGT) and Skin Conductance Response (SCR), found that there was no difference between males and females when SCR was used; however, there was a difference when the IGT was used. They concluded that the perception of women having lower risk tolerance than men is mainly a 'cultural product', not supported by any other biological or behavioral explanation.

Despite inconsistencies in research findings, gender is considered by financial advisors as a key factor in shaping financial planning recommendations. For example, female advisors have a higher tendency to stereotype than their male counterparts (Siegrist, Cvetkovich, & Gutscher, 2002). A study on gender stereotyping suggests that investment advisors have a tendency to underestimate and overestimate the risk tolerance of female and male clients, respectively (Roszkowski & Grable, 2005).

2.9.2 Age. Age is a variable used by both researchers and financial advisors to predict *FRT*. There is a general agreement that financial risk attitudes differ among people based on age (Grable, 2008; Grable et al., 2009a). It is often assumed that individuals prefer to take fewer financial risks as they age because older investors have less time to recover from potential losses incurred with risky investments (Grable & Lytton, 1998; Jianakoplos & Bernasek, 2006). There is also some suggestion that biological changes in enzymes due to the aging process may be responsible for lower risk tolerance (Hallahan et al., 2004; Harlow & Brown, 1990).

However, the results of earlier empirical studies examining the relationship between risk tolerance and age are conflicting. Some (e.g., Cohn et al., 1975; Grable, 2000; Wang & Hanna, 1997) found that risk tolerance increases with age. Using the proportion of net wealth invested in risky assets as an indicator of risk-tolerance, Wang and Hanna (1997) and Gutter (2000) found a positive effect of age on households' risk tolerance. This positive impact may be due to the inclusion of human capital in the net worth calculation. As age increases, the amount of risky assets increases and human wealth decreases. Therefore, the ratio of risky assets divided by net worth, including human capital, increases as people age. Grable and Lytton (1999) also found that older individuals have greater mean risk-tolerance scores than younger subjects.

On the other hand, some researchers (e.g., Ahmad et al., 2011; Finke & Huston, 2004; Gibson et al., 2013; Gilliam et al., 2010b; Grable et al., 2008; Hallahan et al., 2004; Jianakoplos and Bernasek, 2006; Wong, 2011) found that *FRT* decreases with age. According to Grable et al. (2008), older individuals in their study were less likely to be willing to take financial risks. These results were concluded from a study using the 13-item *GL-FRT* scale to measure *FRT*. Most recently, Wong (2011) conducted research using FinaMetrica data from the U.S., the U.K., and Australia and found that age was negatively associated with risk tolerance. There are also several studies that have noted no relationship between age and risk tolerance (e.g., Anbar & Eker, 2010; Arano, Parker, & Terry, 2010; Grable & Lytton, 1998; Grable & Lytton, 1999).

2.9.3 Marital Status. Marital status has moderate support in the literature as a factor associated with risk tolerance. It is often assumed that single individuals are more risk tolerant than married individuals (Grable & Joo, 2004; Grable & Lytton, 1998; Hallahan et al., 2004; Yao & Hanna, 2005; Wong, 2011). Cohn et al. (1975) found that married individuals allocate a smaller proportion of wealth to risky assets. According to Roszkowski, Snelbecker, and Leimberg (1993), this may be due to the level of responsibilities faced by a single person versus a married couple. They argued that a married couple is more apt to have greater financial responsibilities and a presence of dependents, thus leading to less risk tolerance. Moreover, they suggested that married couples may also face more social risk, which can be described as a loss of esteem due to investment failure. Married couples with two incomes, however, may have greater risk tolerance driven by a larger degree of risk capacity.

Hinz, McCarthy, and Turner (1997) found that individuals who were married invested less aggressively than single individuals. Gutter (2000) reported that unmarried males have a higher ratio of risky assets to net worth, and that the ratio was lower for unmarried females than married couples. Ardehali et al. (2005) hypothesized that married individuals may feel that a monetary loss resulting from a financial decision could negatively impact their family and relationship, and as a result, married individuals may shy away from taking risks. However, Wong (2011) reported that of all the demographic variables studied, marital status had the lowest impact on risk tolerance.

On the other hand, Gilliam et al. (2010b), Grable (2000), Hallahan et al. (2004), Venter (2006), Grable and Lytton (2003), and Watson and McNaughton (2007) found that married investors were more risk tolerant than singles. These researchers suggested that married individuals have greater risk taking propensities because shared income and the double human capital of married individuals may encourage them to invest in riskier assets.

In a number of studies, marital status was not found to be a significant determinant of an individual’s attitude towards risk (e.g., Grable & Lytton, 1999; Hallahan et al., 2004; Sundén & Surette, 1998). Some studies (e.g., Deaves et al., 2007; Haliassos & Bertaut, 1995) failed to find any relationship between marital status and risk tolerance.

It is possible that marital status is confounded with other demographic characteristics. For example, Sung and Hanna (1996) found that single females have lower risk tolerance than couples, and couples have lower risk tolerance than single males. Sundén and Surette (1998) concluded that gender interacts with marital status and has an effect on households’ investment choices. They noted that compared with single men, single women and married men were less likely to allocate their assets to “mostly stocks”, which indicates more financial risk.

2.9.4 Education. A person’s level of formal education has been found to influence risk tolerance. It is generally assumed that with more formal education, an individual is better equipped to assess the risk/return trade-off of an investment. Many empirical studies indicate that a positive relationship exists between educational attainment and *FRT* (e.g., Ahmad et al., 2011;

Baker & Haslem, 1974; Gilliam et al., 2010b; Grable & Lytton, 1999; Grable, 2000; Grable & Lytton, 1998; Hallahan et al., 2004; Riley & Chow, 1992; Shaw, 1996; Sung & Hanna, 1996; Wang & Hanna, 1997; Wong, 2011). Haliassos and Bertaut (1995) found that more highly educated households were more likely to own stocks than households with less education. Zhong and Xiao (1995) used the dollar value of stock and bond holdings and found that education had a positive relationship with risk tolerance. Research conducted by Grable and Lytton (1999) indicated that an individual's attained level of education was the best discriminating factor between levels of risk tolerance. However, by studying the ratio of risky assets to net worth, Gutter (2000) noted that education had a negative effect on risk tolerance.

On the other hand, Deaves et al. (2007) tested multiple demographic variables and concluded that there was no support for the relationship between education level and risk tolerance. Similarly, Watson and McNaughton (2007) reported that risk tolerance and education were unrelated. Ho (2009), relying on an experimental study of risk aversion in decision making under uncertainty, concluded that there was no support for a relationship between education and risk tolerance.

2.9.5 Household Income. Household and personal income is a significant factor that is thought to be associated with a person's level of risk tolerance. It is often assumed that *FRT* increases with income. Many researchers have found this positive relationship to be significant (Bernheim, Skinner & Weinberg, 2001; Gilliam et al., 2010b; Grable, 2000; Grable & Lytton, 1998; Hallahan et al., 2004; Riley & Chow, 1992; Schooley & Worden, 1996; Shaw, 1996; Wong, 2011). Roszkowski (1998) noted that what these results may be measuring is risk capacity. A higher income provides an individual greater capacity to incur a risk. Upper-income individuals can more easily afford to sustain losses resulting from a risky investment (Grable &

Lytton, 1998; Hallahan et al., 2004; Watson & McNaughton, 2007). Many research findings support this hypothesis. Cohn et al. (1975) did find that relative risk tolerance (the percentage of income invested in risky assets) also increases with income. Haliassos and Bertaut (1995) found a positive relation between income and risky asset ownership. Shaw (1996) noted that risk tolerance increases with wage growth. Shaw also found that wage growth (income) was positively correlated with risk tolerance. Research conducted by Grable and Lytton (1999) concluded that household income was the most important factor when explaining variance in risk-tolerance scores. Bertaut and Starr-McCluer (2000) found that households were more likely to own stock-based assets as income increases. Deaves et al. (2007) concluded that those who had higher salaries also had higher risk tolerance.

On the other hand, some have noted a negative relationship between *FRT* and income. Cicchetti and Dubin (1994) found that risk tolerance decreases as income increases. Riley and Russon (1995) found that Chartered Financial Analysts believed risk tolerance should decrease with salary growth. Faff et al. (2008) argued that individuals with lower income may be willing to take more risk.

Some researchers have concluded there is not a significant relationship between income and risk tolerance. McInish (1982) noted that income was not a significant factor in explaining risk tolerance. Palsson (1996) concluded that risk tolerance was not systematically correlated with income. Research by Arano et al. (2010) led these researchers to conclude that income did not have a significant association with risk aversion.

2.10 Risk-Tolerance Estimation Error (*RTEE*)

Research shows that some investors will either over or underestimate risk and their tolerance for risk taking (Hilbert, 2012). The literature indicates that younger working adults tend to overestimate their tolerance for risk, while older working adults generally underestimate their *FRT* (Gilliam & Grable, 2010; Grable et al., 2009a). Women can be predicted to underestimate their risk tolerance; men can be predicted to overestimate their tolerance for financial risk (Gilliam & Grable, 2010; Grable & Roszkowski, 2007). Educational status is known to be positively associated with an overestimation of *FRT* (Gilliam & Grable, 2010), and married men tend to be more prone to overestimate their *FRT* (Gilliam & Grable, 2010; Grable et al., 2009a).

Gilliam et al. (2010b) reported a tendency among individuals to underestimate their *FRT*. This tendency to underestimate *FRT* increases with age, and is negatively associated with educational attainment of college or higher, and income. Married respondents and men are known to be less likely to underestimate their *FRT*. Wong (2011) reported that people have a tendency to perceive risk-tolerance lower than what their actual risk-tolerance scores indicate. On average, the perceived score is anywhere from 5.0 to 5.6 points lower than the actual score.

Grable and Rabbani (2014) tested the accuracy level of respondents' estimates of generalized tolerance for risk using the National Longitudinal Survey of Youth data. The tendency to over or underestimate risk tolerance, measured by subtracting predicted risk-tolerance scores from a general risk-tolerance item, represented risk-tolerance estimation error. They found that 19% of respondents did an excellent job of self-evaluating risk tolerance. Forty-one percent underestimated the tolerance for risk, and 40% overestimated their risk tolerance.

Their findings demonstrated that these measurement errors are likely normally distributed with a mean of zero.

Lucarelli et al. (2014) used a psychometrically derived questionnaire based on the *GL-FRT* scale to assess level of estimation error. They found that there was an enormous level of misclassification (i.e., estimation error). Individuals who were asked to self-assess their risk tolerance revealed a high probability of making errors. Lucarelli et al. showed evidence that individuals behave as if they were risk takers while defining themselves as risk averse (and vice versa).

2.11 Summary

It is well documented in the literature that affect plays an important role in decision making. Simon (1983) argued that "in order to have a complete theory of human rationality, we have to understand the role emotion plays in it" (p. 20). Luce, Payne, and Bettman (1999) found that a consumer's desire to avoid negative feelings has an impact on their purchase selection. Thaler (2000) commented on future directions for economic research by arguing that economists will become increasingly interested in the influence of emotions on economic decision-making. Loewenstein, O'Donoghue, and Rabin (2002) and Laibson (2000) outlined many instances of the influence of emotions on economic behavior. For example, gender differences in risk taking may be linked to differences in emotional preparedness; female individuals experience feelings more intensely than males. Moreover, age-based differences in risk taking may be affectively mediated. These observations indicate that the influence of affect may vary with variation in demographic characteristics.

This chapter has explored the relevant literature pertaining to decision-making and feelings. This chapter reviewed theories related to risk tolerance and empirical applications of risk tolerance, risk-tolerance measures, the methodologies used to analyze risk tolerance, the choices of explanatory variables that affect risk tolerance, and empirical findings on risk tolerance. The measures of risk-tolerance used in previous studies are very diverse, resulting in some conflicting findings regarding the effects of some demographic variables on risk tolerance, especially age. However, risk tolerance has been found to be a function of several demographic characteristics; the most commonly cited variables are gender, age, marital status, education, and household income. Hence, these variables were included in this *FRT* research. Previous research on the relationships between *FRT* and demographic variables has focused on the identification of those demographic attributes that significantly impact risk-tolerance scores. There is some evidence that many respondents inaccurately estimate their risk tolerance. The RaF hypothesis suggests that these inaccuracies are more likely due to the influence of affect on risk-tolerance assessment.

Gilliam and Grable (2010), Grable and Roszkowski (2007), Grable et al. (2009a), and Moreschi (2005) are some examples of the studies that investigated *RTEE*. Gilliam and Grable, Grable and Roszkowski, and Grable et al. used cross-sectional questionnaire survey data. Moreschi used FinaMetrica data. The need for another empirical study of the relationships among the demographics of interest in this study (i.e., gender, age, marital status, education and income,) and *AE* is evidenced by several factors: (a) although very common, *RTEE* is not well researched; (b) academic findings in relation to *RTEE* and these demographics have been inconclusive and often conflicting; (c) financial *RTEE* may be a good proxy for measuring *AE* as an element of *FRT*; and (d) there may be an association between *AE* and *PR* scores. Further research is needed to clarify these claims.

A description of the demographic characteristics that are associated with affective evaluation can help advisors demonstrate intuitive and creative strategic thinking in their service to clients. Advisors may also want to understand and discuss a client's risk tolerance under the purview of current research developments in this area. Certainly, the greater an individual's self-understanding of risk tolerance, the easier is the task of educating and advising that client. The remainder of this dissertation is devoted to describing the research methodology and results. The dissertation concludes with a discussion of the findings.

CHAPTER 3

METHODOLOGY

3.1 Overview of Methodology

An important outcome of this study is the development of a methodology to estimate affect (i.e., feelings), use it to describe investors, and understand differences in investor's investment behaviors. The focus of this study is on grouping investors with a similar affective evaluation of risk tolerance. The findings from this research add to the current body of literature about the influence of affect on some types of investor behavior. Specifically, results provide a tool for a financial planner to measure affect associated with a financial risk-tolerance (*FRT*) assessment.

This study was designed to determine the degree to which investors exhibit affect during an evaluation of *FRT*. Here, affect observed in *FRT* was termed as Affective Evaluation (*AE*). For estimation of *AE*, this study relied on the Risk-as Feelings (RaF) hypothesis and Classical Test Theory (CTT). The RaF hypothesis suggests that subjective evaluation (*SE*) of risk consists of objective evaluation (*OE*) and *AE*. In order to measure *AE*, the first step in this study was to determine which items in a risk-tolerance questionnaire (the 13-item *GL-FRT* questionnaire) could be used measure *OE*; the second step focused on which items measure *SE*. The study relied on Exploratory Factor Analysis (*EFA*) to estimate the *SE* and *OE* components from the *GL-FRT* questionnaire.

At the third step, this study developed a method to estimate *AE* based on *SE* and *OE*. Once *OE* and *SE* items were identified, a test was undertaken to estimate *AE* relying on propositions imbedded in CTT, as this measurement theory suggests that, within the context of *FRT* assessment, *SE* may consist of *OE* and *RTEE*. Thus, if *OE* and *SE* are known, then it is reasonable to assume that *RTEE* can be used as an indicator of *AE*. The literature shows that it is possible to estimate *RTEE* from a risk-tolerance questionnaire using a differential prediction model (Gilliam & Grable, 2010; Grable & Roszkowski, 2007; Grable et al., 2009a, Moreschi, 2005). This study advances works of others who have used survey data from the *GL-FRT* scale (Gilliam & Grable, 2010; Grable & Roszkowski, 2007; Grable et al., 2009a) to estimate *RTEE.* The current study used data from the *GL-FRT* scale in an ordinal logistic regression (or *ordinal regression*) analysis to measure *RTEE* as a proxy for *AE.*

In the fourth step, the study looked at whether it is possible to describe each *AE* group by asking what the demographic characteristics of each of the *AE* groups are. The literature suggests that based on estimation errors investors make while assessing their subjective risk tolerance, people can be classified into one of the three groups: (a) overestimation, (b) underestimation, or (c) accurately estimation. Moreover, there is evidence suggesting that demographic variables may be associated with the evaluation of *FRT*. It is, therefore, reasonable to hypothesize that demographic variables may be associated with *AE* groups. This study tested this hypothesis and attempted to describe the *AE* groups using chi-square tests of homogeneity, hierarchical cluster analysis, and an ordinal regression analysis.

In the fifth and final step, the study explored the association between Portfolio Risk (*PR*) scores and *AE* groups while controlling for the effects of demographic characteristics and reliance on professional investment advice. The *PR* score was based on the asset allocation holdings of respondents. The association between *PR* score and *AE* group membership was assessed using an OLS regression analysis, where variables were entered into the model as follows: *PR* score as a dependent variable, *AE* groups as independent variables, and demographic characteristics and reliance of professional advice as control variables.

3.2 Research Questions

This study attempted to quantify affect (i.e., feelings) within the context of RaF hypothesis and CTT. Additionally, this study divided individual investors into different groups based on *AE*. The study further looked at the differences in demographic characteristics of *AE* groups. The final aim was to examine the association between *AE* and *PR* scores. This study attempted to answer the following specific research questions:

(1) Can items be identified that measure objective risk-tolerance reliably as a proxy for *OE*?

(2) Can items be identified that measure subjective risk-tolerance reliably as a proxy for *SE*?

(3) Can *SE* and *OE* be used to derive an estimation of affect (*AE*)?

(4) Can groups of *AE* be described based on investors' demographic characteristics?

(5) Is there an association among *AE* categories and investors' behavior, such as, *PR* score?

3.3 Data and Sample

Data for this research study were obtained from a multi-year data collection project sponsored by Rutgers New Jersey Agricultural Experiment Station. For nearly 10 years, Rutgers University has hosted a free web-based site (http://njaes.rutgers.edu/money/ riskquiz/) that allows any web user to answer the Grable and Lytton risk-tolerance (*GL-FRT*) scale items (Appendix A). The *GL-FRT* scale has been reported to have acceptable scale reliability (Kuzniak, Rabbani, Heo, Ruiz-Menjivar, & Grable, 2015) with a Cronbach's alpha of 0.77.

Reliability estimates provide an indication of how consistent responses have been over time. Cronbach's alpha represents the lower bound of reliability (Cortina, 1993). Peterson (1994) noted that the average reported Cronbach's alpha in the psychological and marketing literature ranges from 0.76 to 0.77. Scores below $\alpha = 0.70$ are considered to be useful only in exploratory studies. Gilliam et al. (2010a) also conducted a concurrent validity test of the *GL-FRT* scale. They correlated the measure against responses to the SCF risk item; they reported a statistically significant correlation ($r = 0.60$). Validity tests conducted by Kuzniak et al. (2015) also demonstrated that scores on the *GL-FRT* scale were positively associated with equity ownership and negatively related to cash and fixed-income ownership. They concluded that the *GL-FRT* scale offers users an economical way to differentiate between individuals who are more or less likely to take financial risk.

The original dataset contained response data from over 200,434 individuals, beginning in late 2007 and ending in early 2014. This original dataset was subjected to a data cleaning process that involved removal of observations with missing values and foreign language responses. The sample was delimited to only those with at least some investment assets. The dataset was further delimited to respondents who had complete responses to the investment assets class questions in the survey (Items 19a, 19b, 19c, & 19d). The final cleaned and delimited dataset included 108,065 respondents. Initially, a sample of 10,806 respondents was randomly selected. The preliminary descriptive analysis showed that the data were highly skewed towards a younger sample (less than and equal to 34) (Skewness = 1.59) (Figure 3.1). A further delimitation of this sample was made to exclude very young respondents. This improved the normality of the data, and made the dataset more generalizable for financial planners. For example, previous literature reported that respondents under age 35 are less likely to hold a retirement account (Glumov, 2013). Therefore, a reduced sample of 3,975 that included respondents over age 34 was used in this study. The demographic variables of gender, age, marital status, education, and household income were coded as dummy variables. Table 3.1 summarizes the descriptive characteristics of the sample. A discussion of each variable follows.

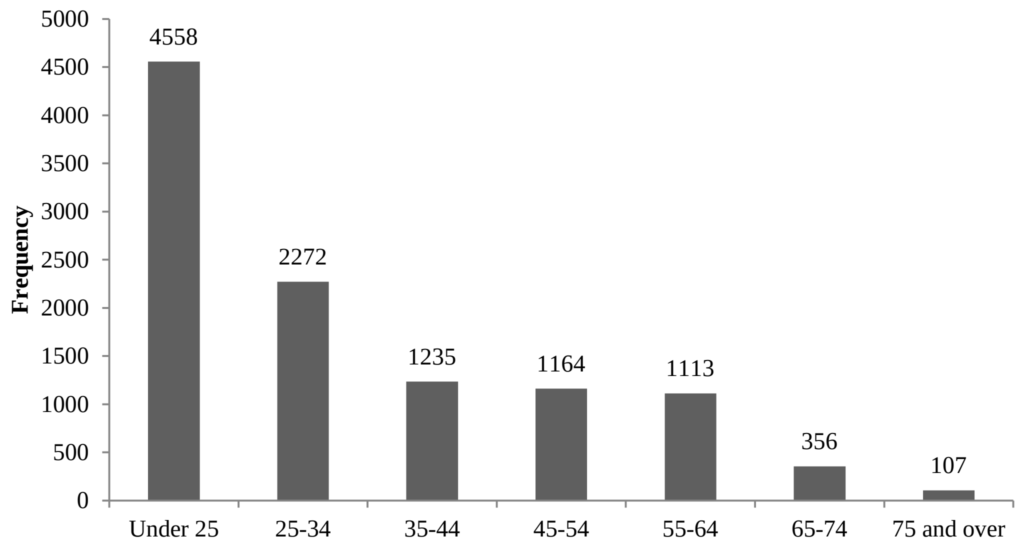

Figure 3.1 Skewness to younger respondents.

3.3.1 Gender. Gender was coded as 1 = Female; 0 = Male. The reference category was male. Gender has been previously reported to be associated with variations in *RTEE* (Gilliam & Grable, 2010; Grable et al., 2009a; Grable & Roszkowski, 2007; Moreschi, 2005). In the sample, there were more males (63%) than females (37%).

3.3.2 Age. The age of respondents was measured with a categorical variable: (a) 35 to 44, (b) 45 to 54, (c) 55 to 64, (d) 65 to 74, and (e) 75 and over. Dummy coding of the age variable was applied as follows: (a) 35-44 = 1 if respondent fell into this age group, 0 otherwise; (b) 45-54 = 1 if respondent fell into this age group, 0 otherwise; (c) 55-64 = reference category; (d) 65-74 = 1 if respondent fell into this age group, 0 otherwise; (f) above 75 = 1 if respondent fell into this age group, 0 otherwise. Approximately one-third of the sample were 35 to 44 years old.

Table 3.1

Sample Descriptive Statistics

	Respondents (n = 3,975)	%
Male	2503	62.97%
Female	1472	37.03%
35-44	1235	31.07%
45-54	1164	29.28%
55-64	1113	28.00%
65-74	356	8.96%
75 and over	107	2.69%
Married	2807	70.62%
Separated or Divorced	494	12.43%
Never married	384	9.66%
Not married but living with significant other	141	3.55%
Widowed	111	2.79%
Shared living arrangement	38	0.96%
Graduate or professional degree	1444	36.33%
Bachelor’s degree	1279	32.18%
Some college/trade/vocational training	693	17.43%
Associate degree	319	8.03%
High school graduate	200	5.03%
Some high school or less	40	1.01%
$100,000 or greater	1822	45.84%
$50,000 to $74,999	774	19.47%
$75,000 to $99,999	714	17.96%
$25,000 to $49,999	525	13.21%
Less than $25,000	140	3.52%

3.3.3 Marital status. The marital status of respondents was assessed with the following categories: (a) Married, (b) Never married, (c) Not Married but living with significant other, (d) Separated or Divorced, (e) Shared living arrangements, and (f) Widowed. This variable was dummy coded as follows: (a) Married = reference category; (b) Never married = 1 if respondent fell into this group, 0 otherwise; (c) Not married but living with significant other = 1 if respondent fell into this group, 0 otherwise; (d) Separated or Divorced = 1 if respondent fell into this group, 0 otherwise; (e) Shared living arrangement = 1 if respondent fell into this group, 0 otherwise; and (f) Widowed = 1 if respondent fell into this group, 0 otherwise. The majority of the respondents (71%) were married.

3.3.4 Education. Education was assessed as a categorical variable and operationalized with answers to the following question: “What is the highest level of education you have completed?” Response options included: (a) Some high school or less, (b) High school, (c) Some college/trade/vocational training, (d) Associate degree, (e) Bachelor’s degree, and (f) Graduate degree. The dummy coding of this variable included: (a) Some high school or less = 1 if respondent fell into this group, 0 otherwise; (b) High school = 1 if respondent fell into this group, 0 otherwise; (c) Some college/trade/vocational training = 1 if respondent fell into this group, 0 otherwise; (d) Associate degree = 1 if respondent fell into this group, 0 otherwise; (e) Bachelor’s degree = 1 if respondent fell into this group, 0 otherwise; and (f) Graduate degree = reference category. The sample were well educated. The majority of the respondents (69%) have earned Bachelor’s degree or higher.

3.3.5 Household income. Household income was measured as a categorical variable. Data for this variable came from responses to the following question: “What is your household's approximate annual gross income before taxes?" The response categories included: (a) Below $24,999, (b) $25000 to $49,999, (c) $50000 to $74,999, (d) $75,000 to $99,999, and (e) Over $100,000. This variable was dummy coded as follows: (a) Below $24, 999 = 1 if respondent fell into this group; 0 otherwise; (b) $25000-$49,999 = 1 if respondent fell into this group, 0 otherwise; (c) $50000-$74,999 = 1 if respondent fell into this group, 0 otherwise; (d) $75,000-$99,999 = 1 if respondent fell into this group, 0 otherwise; and (e) Over $100,000 = reference category. The majority of the respondents (46%) had income of $100,000 and over.

3.4 Data Analysis Procedures

Data analyses were used to: (a) identify of *OE* and *SE* (b) estimate of *AE*, (c) describe of *AE* groups, and (d) test the association between *AE* and *PR* scores. Each step and associated statistical procedure is discussed below.

3.4.1 Identification of *OE* and *SE*. For the estimation of affect, this study first measured objective evaluation of risk tolerance (*OE*) and subjective evaluation of risk tolerance (*SE*). Each is discussed below.

Objective evaluation (OE) of risk tolerance. The objective evaluation (*OE*) of *FRT* was calculated using an adaptation of the *GL-FRT* scale. Guillemette and Finke (2014) argued that a valid and reliable scale can be used as an indicator of a person's *OE*. To determine which items of the 13-item *GL-FRT* scale were most relevant as *OE* questions an Exploratory Factor Analysis (*EFA*) was performed. A presence of objective (items requiring cognitive evaluation) and subjective (items requiring perception and subjective evaluation) items in each component was explored. A structure matrix of the *EFA* was used to explore if a component had more objective items than subjective items.

In summary, *EFA* with nine cognitive assessment items was also conducted. A reliability test was conducted. A validity test was conducted by exploring the correlation between the *OE* score based on cognitive assessment items with actual *PR* scores. It was hypothesized that there should be a positive relationship, since, *PR* scores in previous literature were considered as indicators of objective measures of financial risk. Finally, each respondent's *OE* was measured using a 9-item risk-tolerance scale. The scale consisted of multiple-choice items that require respondents to choose among outcomes that reflect different financial risk. Items in the scale assessed attitudes and behaviors related to stock and bond investing, options and commodity investing, gambling, and risk avoidance.

Subjective evaluation (SE) of risk tolerance. The subjective evaluation of FRT was calculated by recording each respondent's answer to the following question: "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; or (d) A real risk avoider." This is the first question (Item 1) in the *GL-FRT* scale (Appendix A). Scores were assigned as follows: Real gamblers received a score of 4.0; those who were willing to take risks after adequate research received a score of 3.0; those who were cautious received a score of 2.0; and real risk avoiders received a score of 1.0. Higher scores represented higher risk tolerance. Grable et al. (2009b) tested the validity of this question with the result being that it served well as a quick, one-time risk-assessment tool.

3.4.2 Estimation of affective evaluation (*AE*) of risk tolerance. *AE* was estimated with a differential prediction model. In the model, *AE* within the sample was measured using *OE* and *SE* scores. Because of the ordinal coding of the *SE* variable, an ordinal regression model was used to predict each respondent's *SE* score from *OE* scores (Equation (*v*)). Moreschi (2005), Gilliam and Grable (2010), Grable and Roszkowski (2007), and Grable et al. (2009a) used a similar model to estimate errors in self-evaluated risk attitude.

$SE_i = \alpha_i + \beta\,(OE) + e_s$……………………. *(v)*

Where, *SE* = subjective evaluation, *OE* = objective evaluation, α = constant, β = regression coefficient, and e_s = error associated with the objective evaluation. It follows from the conceptual model described in Chapter 1, and Equation (*iv*), $AE = -e_s$, when $SE = OE$. This means that when *SE* is aligned with *OE*, *AE* of risk tolerance has an equal and opposite relationship with the model's systematic error (e_s). Therefore, Equation (*v*) becomes

$SE_i = \alpha_i + \beta\,(OE) - AE$

$AE = (\alpha_i + \beta\,(OE)) - SE_i$……………………………….*(vi)*

The (α + β (*OE*)) part of the Equation (*vi)* is the predicted category *SE* ($SE_{Predicted}$); therefore, Equation (*vi*) is,

$AE = SE_{Predicted} - SE$……………………………….*(vii)*

The predicted category ($SE_{Predicted}$) from the regression was saved for all respondents. Each respondent's *SE* was then subtracted from their predicted risk-tolerance score ($SE_{Predicted}$) (Equation *vii*). The result was an *AE* estimate for each respondent that indicated the amount by which a respondent either overestimated or underestimated their psychometrically assessed risk-tolerance (Linn, 1978). A positive (+) residual value indicated the suppressing effect of affective evaluation. This also suggested underestimation. A negative (-) residual value indicated a reinforcing effect of affective evaluation on objective evaluation. This also suggested overestimation. A score of zero indicated that objective and affective processes were in equilibrium. This interpretation is different from previous literature; for example, Grable and Roszkowski (2007) defined the residual value as self-rating less predicted self-rating, which is just opposite of the formula used in this study. As a result, a positive residual value in Grable and Roszkowski's study was interpreted as overestimation of risk tolerance and a negative residual value as underestimation.

Based on *AE* scores, respondents were combined into six *AE* groups. It is important to note that *AE* was not the error term of the functional relationship, where risk-tolerance score (RTS) = *f* (demographic variables). Rather, given that the risk-tolerance questionnaire was assumed to be robust (i.e., valid and reliable, meeting psychometric standards), $SE_{Predicted} - SE$ was defined as a measure of *AE* among respondents when asked to provide a self-assessment.

3.4.3 Description of *AE* groups. In this study, demographic variables (e.g., gender, age, marital status, education, and household income) were used to describe the *AE* groups. The demographic variables were used in a chi-square test of homogeneity, ordinal regression analysis, and cluster analysis.

Chi-square test of homogeneity. A chi-square test for homogeneity was used in this study to test if there was a relationship among *AE* groups and demographic characteristics. Prior to using this test, data were checked for appropriateness using two assumptions. First, the variables needed to be measured at an ordinal or nominal level. Second, the variables needed to consist of two or more categorical, independent groups. In SPSS 22.0, this test was run from the Crosstabs function of the Descriptive Statistics menu. For the chi-square tests, the demographic variables that were coded as nominal variables were used.

Ordinal regression. An ordinal regression analysis was used in this study to test if there was any association between *AE* group membership and the demographic variables. Ordinal regression is a specialized case of a generalized linear model where ordering of the outcome variable is taken into account. In this study, there was an ordering among the outcome variable (*AE* groups). In the ordinal regression analysis, each demographic variable was coded as a group of dummy variables. The model is as follows:

$$ln\left(\frac{prob\ (AE\ group_i)}{1-prob\ (AE\ group_i)}\right)$$
$$= \alpha_i + \beta_{1j}D_{Gender} + \beta_{2j}D_{Age} + \beta_{3j}D_{Marital} + \beta_{4j}D_{Educ} + \beta_{5j}D_{Income} + \mu_i$$

Where,

D_{Gender} is the dummy variable for gender; male is the reference category;

D_{Age} are the dummy variables for age categories; age 55-64 was the reference category;

$D_{Marital}$ are the dummy variables for marital status; married was the reference category;

D_{Educ} are dummy variables for education status; graduate education was the reference category;

D_{Income} are dummy variables for household income; income more than $100 thousand was the reference category; and

μ_i is the error term.

Hierarchical cluster analysis. The study attempted to describe *AE* groups using a cluster analysis relying on *AE* scores and the demographic characteristics of respondents. Cluster analysis involves a series of decisions from variable selection to algorithm selection. Based on the review of literature, the following variables were used in the cluster analysis: *AE*, age, gender, marital status, income, and education. In the cluster analysis, each demographic variable was treated as a group of dummy variables. This approach was taken because, when represented using a continuous variable, the distance between (1) and (3) is twice as large as the distance between (1) and (2). The clustering algorithm thus considers these to be more dissimilar. This difference is not an issue when a variable is coded as a dummy variable, where the distance is in fact binary. Hierarchical clustering was used in this study because it does not require a researcher to pre-specify the number of clusters. The optimal number of clusters were determined, using a Dendrogram, which visualizes the variation within the clusters for different steps of the clustering procedure. In this study, a similarity measure, such as correlation, was used because there were several variables that were measured on a categorical scale. This research applied Ward’s algorithm for clustering because this method uses an analysis of variance approach to evaluate the distances between clusters.

3.4.4 Association between *AE* and *PR*. For this analysis, *AE* groups, *PR* scores, demographic variables, and reliance on professional advice variable were used. The analyses were conducted using two methods: ANOVA and OLS regression analysis. *PR* scores were based on four investment allocation categories “cash”, “fixed”, “stock”, and “other” and used in both tests. These categories were derived from the following question, “Thinking about your current financial situation, approximately what percentage of your personal and retirement savings and investments are in the following categories?” The categories included: (a) “Cash”, such as savings accounts, CDs, or money market mutual funds; (b) “Fixed” income investments, such as corporate bonds, government bonds, or bond mutual funds; (c) “Equities”, such as stocks, stock mutual funds, direct business ownership or investment real estate (not your personal residence); and (d) “Other”, such as gold or collectibles. Percentages were evaluated as continuous variables measured on a ratio scale. On average, an investor in the sample had an investment asset allocation similar to the one shown in Figure 3.2. Cash was the largest holding, while equities was the second largest category.

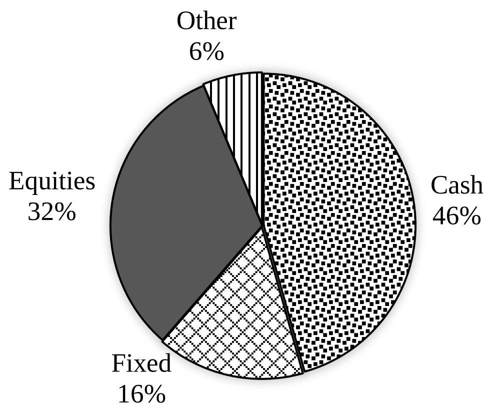

Figure 3.2. Average investment asset allocation of respondents.

For the purpose of the present study, *PR* score was used to determine whether investment choices varied among the groups. A measure of *PR* score for each investor was calculated using the riskiness weights for each asset category above because riskiness varies among different asset categories (Corter & Chen, 2006). The present research used weights as suggested by Corter and Chen (2006): (a) cash (0.0), (b) fixed (0.12), (c) equities (0.2), and (d) other (0.12). Specifically, each category's risk weighting was multiplied by the percentages of the investor's assets invested in that category,

$$PR = \sum r_i p_i, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (viii)$$

where *PR* is the overall portfolio risk score for an investor, r_i is the risk weighting of the asset category, and p_i is the percentage of the investor's assets invested in that asset categories.

One-way analysis of variance. A one-way analysis of variance (ANOVA) function within SPSS 22.0 was used to determine whether there were any significant differences among the *AE* groups based on mean *PR* score. Before applying ANOVA, ANOVA assumptions were tested with *PR* data. One limitation of ANOVA is that it cannot identify which specific groups that are significantly different from each other; the test only shows that at least two groups are different. Since there were multiple *AE* groups in this study, determining which of these groups differed from each other was important. For this purpose, Tukey's test was used as a post-hoc evaluation method.

Ordinary Least Square (OLS) regression analysis. An OLS regression was conducted using *PR* score as a dependent variable and demographic characteristics as control variables. The analysis also included each respondent's reliance on professional advice to control for the influence of working with a financial planner. For simplicity, the analysis consolidated the three positive *AE* groups into one group and the two negative *AE* groups into one group. The *AE* group with a score of zero was used as a reference category. For this analysis, dummy coded demographic variables were used. Reliance on advice of a professional was measured using the following question: "Who is responsible for investment allocation decisions in your household?" Response options included: (a) I, and/or someone in my household, make these decisions; or (b) I rely on the advice of a professional (e.g., broker, financial planner, or other consultant). This variable was coded as "I rely on the advice of a professional" = 1 and 0 otherwise. "I, and/or someone in my household makes these decisions" was the reference category. The OLS regression model was specified as follows:

$$PR = \alpha + \beta_{1j}D_{AE} + \beta_{2j}D_{FP} + \beta_{3j}D_{Gender} + \beta_{4j}D_{Age} + \beta_{5j}D_{Marital} + \beta_{6j}D_{Educ} + \beta_{7j}D_{Income} + \mu_i$$

Where,

PR = Portfolio Risk scores

D_{AE} are the dummy variables for *AE* groups; *AE* = 0 was the reference category;

D_{FP} is the dummy variables for reliance of professional advice; “I, and/or someone in my household makes these decisions” was the reference category;

D_{Gender} is dummy variable for gender; male was the reference category;

D_{Age} are the dummy variables for age categories; age 55-64 was the reference category;

$D_{Marital}$ are the dummy variables for marital status; married was the reference category;

D_{Educ} are dummy variables for education status; graduate education was the reference category;

D_{Income} are dummy variables for household income; income more than $100 thousand was the reference category; and

μ_i is the error term.

3.5 Summary

The purpose of this study was to develop a methodology to estimate affect or feelings as a component of a person’s risk-tolerance assessment. A second purpose was to use the estimate to describe investors and understand differences in their investment behaviors. The four research questions and associated analytical methods are summarized in the Figure 3.3. A questionnaire created by Grable and Lytton (1998) was used to estimate *SE* and *OE*. The Grable and Lytton questionnaire also served as the source for demographic data as described in the definition of variables. Two theories (i.e., RaF hypothesis and CTT) were utilized to guide the estimation of *AE* scores and the development of *AE* groups. After that, *AE* groups, gender, age, marital status, education, and income were tested to determine if these factors can be used to describe *AE* groups. A hierarchical cluster analysis procedure was also employed to describe the *AE* groups. These *AE* groups were then used to test differences in investment behaviors. The findings from this study provide financial planners a tool for estimating affect (i.e., *AE*). Financial planners may use findings to assist clients make more informed decisions. The information is helpful for investors, as well those who are increasingly responsible for their own investment decisions. The following chapters of this dissertation detail findings, conclusions, recommendations, and implications.

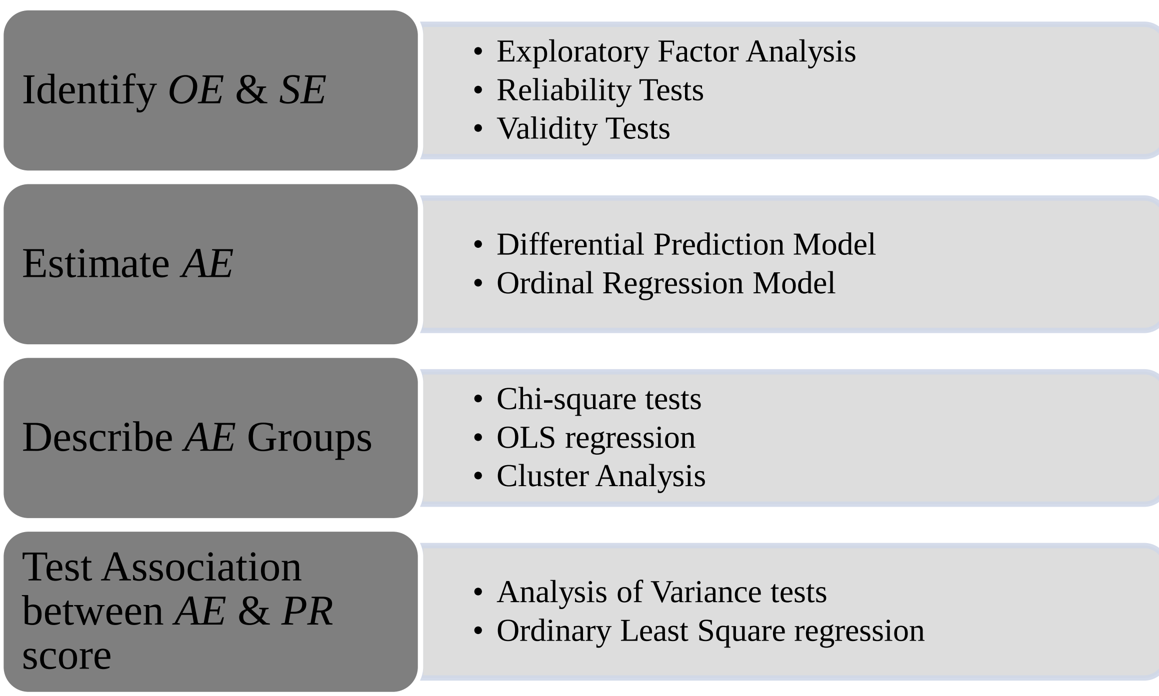

Figure 3.3. Schematic diagram of methodology.

CHAPTER 4

RESULTS

4.1 Overview of Results

This study was designed to develop a methodology to estimate affect (i.e., feelings), use affect to describe investors, and to better understand the association between affect and investor's investment behaviors. A model for estimating affect using the responses from the Grable and Lytton Financial Risk Tolerance (*GL-FRT*) questionnaire was developed and empirically tested using delimited data from the Rutgers New Jersey Agricultural Experiment Station Investor Risk Tolerance database for the period of 2007 to 2014 (N = 3,975). People who did not have investment assets were not included in the analysis; data were also delimited to respondents older than 34 years.

This chapter presents results and findings associated with the four specific research questions. The first research question was related to how Subjective Evaluation (*SE*) and Objective Evaluation (*OE*) can be measured so that these measures can be used in Affective Evaluation (*AE*) estimation. To answer this question, two Exploratory Factor Analysis (*EFA*) tests, using *GL-FRT* data, were conducted to distinguish *SE* and *OE*. The analysis then proceeded to answer the second research question that asked how *SE* and *OE* could be used to estimate *AE*. In the process of answering this question, the study developed a methodology to estimate *AE* based on a differential prediction model using an ordinal regression analysis. This analysis was followed by a series of statistical analyses (i.e., chi-square test of homogeneity, cluster analysis, and regression analysis) using demographic characteristics to describe each *AE* group, which answered the third question that asked how *AE* groups can be described based on demographic characteristics. Finally, the chapter reports the findings of an OLS regression analysis that examined the relationship between *AE* groups with Portfolio Risk (*PR*) scores controlling for demographic variables and reliance on professional advice to answer the fourth research question that asked if investors' *PR* scores differed among the *AE* groups. The following findings are reported: (a) *EFA* results of the 13-item *GL-FRT* measure to determine *OE* and *SE* scores; (b) *EFA* results of 9-items used for *OE*; (c) validity and reliability tests results of *OE*; (d) ordinal regression analysis results of *SE* and *OE*; (e) results from the differential prediction model to measure *AE*; (f) chi-square tests of homogeneity of demographic characteristics results; (g) ordinal regression analysis results of *AE* and demographic characteristics;(h) cluster analysis results using *AE* and demographic characteristics; and (i) OLS regression analysis results of *PR* scores using *AE* groups as independent variables and demographic characteristics and reliance on professional advice as control variables.

4.2 Measurement of *OE*

The first research purpose of the study was to determine if items could be identified from the *GL-FRT* questionnaire that measured objective risk-tolerance reliably as a proxy for *OE.* To answer this question, the study relied on the Risk-as-Feelings (RaF) hypothesis to explore the presence of *OE* in the *FRT* assessment. This hypothesis suggests that a decision maker's *SE* may be composed of both *OE* and the *AE*. An *EFA* of *GL-FRT* scores based on 13 items showed that there were two principal components (Figure 4.1). The coefficients of Kaiser-Meyer-Olkin Measure of Sampling Adequacy (0.87) and Bartlett's Test of Sphericity (Chi-Square = 20768.85) were within acceptable ranges. The analysis used a Principal Component Analysis technique as an extraction method and Oblimin as a rotation method with an eigenvalue of 1 criterion. The total variance explained by the two principal components was approximately 37% (Appendix A). In summary, the results indicated that there was a dichotomous process within the questionnaire that represents *FRT* assessment.

The factor structure matrix that represents the correlations between the variables and the factors showed that the first component represented mainly the cognitive assessment items (i.e., evaluations based primarily on cognitive factors). According Loewenstein et al. (2001), cognitive evaluation means evaluation of severity and probability of the outcome of choice alternatives through some calculation based on expectation before arriving at a decision. Cognitive evaluations have several elements: (a) probability of the outcome, (b) choice alternatives, and (c) expectation based calculation. In the *GL-FRT* questionnaire, there were 9 such cognitive assessment items (Items 2, 4, 7, 8, 9, 10, 11, 12, and 13). Hence, an *OE* scale was developed with these items.

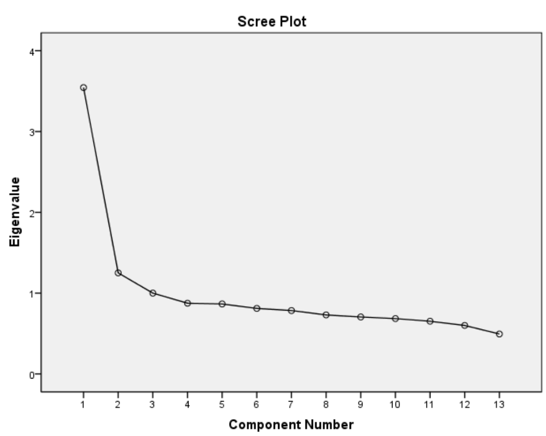

Figure 4.1. Factor analysis scree plot of 13-item *GL-FRT* score.

A further *EFA* on these nine items (Items 2, 4, 7, 8, 9, 10, 11, 12, and 13) showed the presence of a single component (Figure 4.2) that supported the use of these items in developing a composite *OE* scale. The analysis used a Principal Component technique as an extraction method and Oblimin as a rotation method with an eigenvalue of 1. A closer look at these items revealed that Items 9 and 10 were very similar. Item 9 asked, "In addition to whatever you own, you have been given $1,000. You are now asked to choose between: (a) A sure gain of $500; (b) A 50% chance to gain $1,000 and a 50% chance to gain nothing." Item 10 asked, "In addition to whatever you own, you have been given $2,000. You are now asked to choose between: (a) A sure loss of $500; or (b) A 50% chance to lose $1,000 and a 50% chance to lose nothing." These items share the same cognitive evaluation elements: (a) probability of the outcome (sure loss and 50/50), (b) choice alternatives (same two choices), and (c) expectation based calculation. The difference was the initial amount given ($1,000 for Item 9 and $2,000 for item 10) and the way the choices were framed. Item 9 was framed in the domain of gains, whereas Item 10 was framed in the domain of loss. Due to their similarity in cognitive assessment criteria, an average score of Items 9 and 10 was used when developing the *OE* scale.

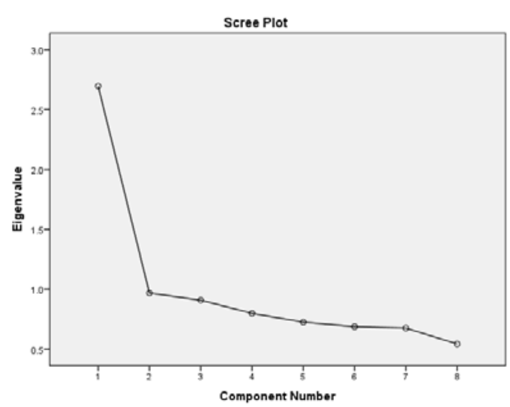

Figure 4.2. Factor analysis scree plot of items used in *OE*.

A reliability test of the 8 items, with an average of item 9 and item 10, resulted in a Cronbach's alpha of 0.71. Therefore, a score based on items that assess monetary return choices and decision-making involving estimation of probability was deemed to be a reliable instrument for measuring *OE*. A further test of the validity of this score was conducted to check if it was measuring what it was intended. In much of the finance literature (e.g., Chang, DeVaney, & Chiremba, 2004; Corter & Chen, 2006) actual *PR* score is considered to be a measure of objective risk tolerance. If *OE* scores, based on the new scale, measured objective evaluation of *FRT*, then it was hypothesized that scores should show a positive relationship with actual *PR* scores demonstrated by the respondents. To test this assumption, a correlation analysis of *OE* with actual *PR* scores was conducted. Results showed that there was a significant positive correlation (Pearson's $r = 0.281$, $\alpha = 0.01$) between the two variables. This means that *OE* and *PR* scores moved in the same direction; therefore, *OE* was deemed acceptable as a measure of a respondent's objective assessment of risk tolerance.

The 8 cognitive assessment items from the *GL-FRT* scale were then combined to estimate *OE*, where item 9 and 10 were averaged. Scores on the *OE* scale ranged from 8 to 29. Higher scores were descriptive of increased objective evaluation of *FRT*. Scores ranging from 8 to 10 indicated a low tolerance for risk; scores of 11 to 14 indicated a below-average tolerance for risk; scores of 15 to 20 indicated an average/moderate tolerance for risk; scores of 21 to 24 indicated an above-average tolerance for risk; and scores of 25 to 29 indicated a high tolerance for risk. As expected, the majority respondents exhibited average risk-tolerance scores (Figure 4.3). The mean and standard deviation of *OE* for the sample (n = 3,975) who were older than 34 years was 16.75 (± 3.49). The maximum *OE* score was 29; the minimum was 8. The *OE* scores were nearly normally distributed (Figure 4.4).

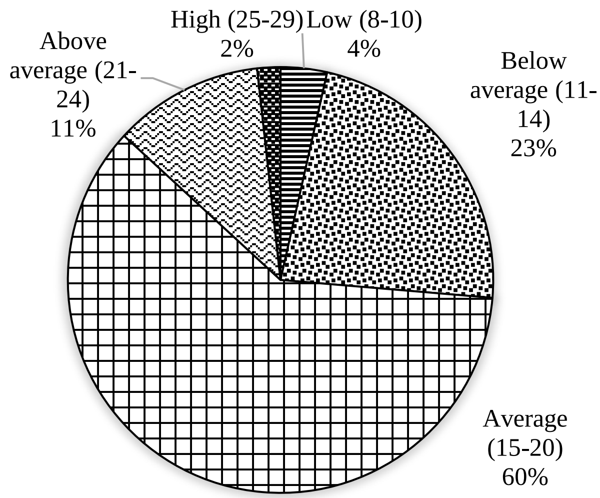

Figure 4.3. Distribution of respondents by risk categories based on *OE*.

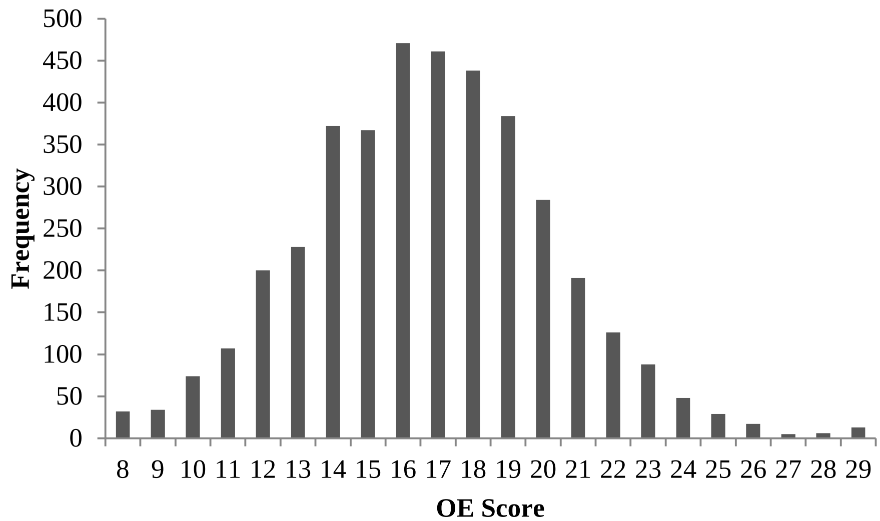

Figure 4.4. Frequency distribution of *OE* scores.

4.3 Measurement of *SE*

Item 1 of the *GL-FRT* scale was used to measure *SE*. This item asked: "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; or (d) A real risk avoider.” The validity of this question has been tested previously with the result being that it served well as a quick, one-time risk-assessment tool (Grable et al., 2009b). Scores were assigned as follows: Real gamblers received a score of 4.0; those who were willing to take risks after adequate research received a score of 3.0; those who were cautious received a score of 2.0; and real risk avoiders received a score of 1.0. The *SE* mean and standard deviation for the sample was 2.59 (± 0.65). As shown in Figure 4.5, most of the respondents in the sample were moderate risk takers (cautious and willing

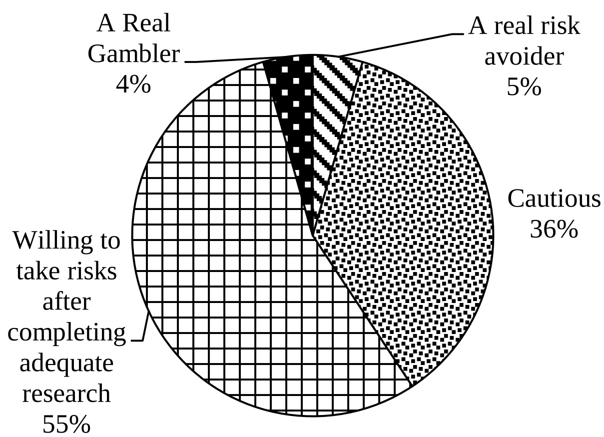

Figure 4.5. Subjective evaluation of the respondents.

to take risk after adequate research). The majority 55% viewed themselves as being willing to take risks after completing adequate research. Approximately 36% of respondents indicated that they were cautious. Of respondents, 5% indicated that they were risk avoiders with 4% viewing themselves as real gamblers.

4.4 Estimation of *RTEE* as a Proxy for *AE*

The third research question of the study asked if *SE* and *OE* can be used to derive an estimation of affect (*AE*). Chapter 3 described the methodology to estimate *AE* using the equation $AE = SE_{Predicted} - SE$, where $SE_{Predicted}$ is the predicted value of *SE* based on *OE*. To sum up, the estimate of *AE* involved the estimation of *OE*, *SE*, and $SE_{Predicted}$. The estimations of *OE* and *SE* were described in the previous sections of 4.2 and 4.3. The following subsections present the empirical test results related to measuring predicted *SE* and *AE*.

4.4.1 Measurement of predicted *SE*. *AE* within the sample was measured using the more reliable *OE* score to predict scores on the single item *SE* question. This method is a differential prediction modeling technique, which is similar to what others have utilized in previous studies to measure predicted *SE*. The *OE* score was considered to be an accurate measure of a respondent's objective *FRT*, whereas *SE* was assumed to provide an estimate of each respondent's subjective assessment of their risk tolerance. Because of the ordinal coding of the *SE* question, an ordinal regression was conducted, where *SE* was used as the dependent variable and *OE* was used as the independent variable. The predicted *SE* and the predicted probability of the regression were saved for all respondents. *SE* predictions were as follows (Figure 4.6): 63.9% were willing to take risks after completing adequate research, 35.6% were cautious, 0.5% were a real gambler, and no respondent was predicted to be real risk avoider. Overall, the ordinal regression model for *SE* was statistically significant (Chi-square = 919.81, $p < 0.001$) with approximately 24% of variance explained by the model (Nagelkerke pseudo R-square). Table 4.1 shows the coefficient estimates of the ordinal regression analysis. In ordinal regression, threshold estimates are intercept (α_i) terms and location estimates are coefficient (β_j)

terms. Each logit has its own intercept (α_i) estimate but the same coefficients (β_j). For example, α for *SE* = 1, *SE* = 2, and *SE* = 3 were -7.543, -4.449, and -0.411 respectively. The threshold values do not depend on the values of the independent variables. They were used in the calculations of predicted values.

Table 4.1

Ordinal Regression Analysis Results

SE	Threshold Estimate	*OE*	Location Estimate
SE = 1	-7.543***	*OE* = 8.00	-6.772***
SE = 2	-4.449***	*OE* = 9.00	-6.862***
SE = 3	-0.411	*OE* = 10.00	-6.171***
SE = 4	Reference	*OE* = 11.00	-5.803***
		OE = 12.00	-5.472***
		OE = 13.00	-5.167***
		OE = 14.00	-4.763***
		OE = 15.00	-4.515***
		OE = 16.00	-4.201***
		OE = 17.00	-3.948***
		OE = 18.00	-3.626***
		OE = 19.00	-3.404***
		OE = 20.00	-2.952***
		OE = 21.00	-2.654***
		OE = 22.00	-2.600***
		OE = 23.00	-2.489***
		OE = 24.00	-1.504*
		OE = 25.00	-1.459*
		OE = 26.00	-0.936
		OE = 27.00	-1.553
		OE = 28.00	19.88
		OE = 29.00	Reference

*$p < 0.05$. ***$p < 0.001$

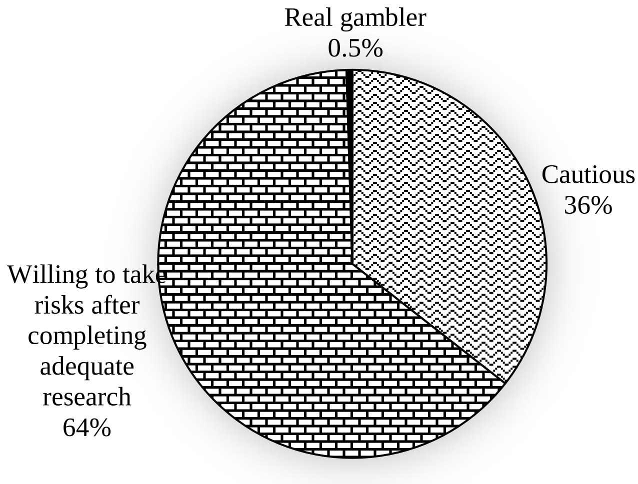

Figure 4.6. Predicted subjective evaluation of the respondents.

4.4.2 Measurement of *AE*. *AE* scores were estimated by taking the difference between predicted *SE* obtained from the differential prediction model and observed *SE*. The sign (positive or negative) of the *AE* indicates whether a respondent overestimated or underestimated his/her risk tolerance. A positive sign indicated that their predicted *SE* was greater than their observed *SE*, thus indicating that the respondent underestimated his/her *SE* compared to their predicted *SE*. On the other hand, a negative sign indicated overestimation of *SE*. This is different from previous studies where a positive residual value was interpreted as overestimation of risk tolerance and a negative residual value as underestimation (see Grable & Roszkowski, 2007). This is primarily because Grable and Roszkowski and others estimated the residual value as self-rating less predicted self-rating, whereas in this study it was calculated as predicted SE minus self-rating. A frequency distribution of *AE* showed there were six *AE* groups (Figure 4.7). There were two groups with negative *AE* scores, one with zero *AE* scores, and three groups with positive *AE* scores. About 64% of the respondents' *SE* matched with the *SE* predicted by the differential prediction model (i.e., *AE* = 0). Approximately 21% of the respondents' predicted *SE* was higher than their own *SE* (i.e., positive *AE*) and approximately 15% of the respondent's predicted *SE* was lower than their own *SE* (i.e., negative *AE*).

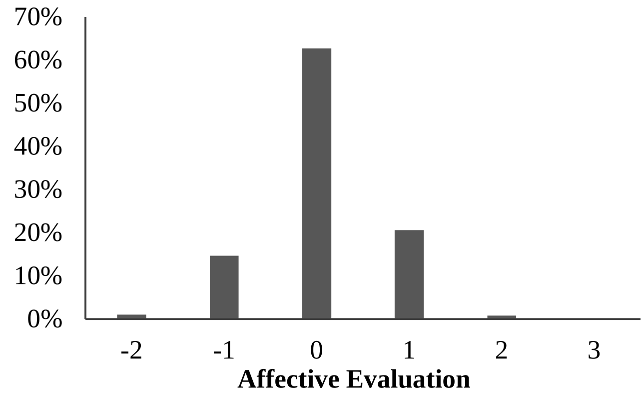

Figure 4.7. Distribution of affective evaluation (*AE*).

4.5 Demographic Description of *AE* Groups

The fourth research question of the study asked if categories of AE can be described based on investors' demographic characteristics. The initial data distribution showed that there were six *AE* groups based on the following scores: *AE* = -2; *AE* = -1; *AE* = 0; *AE* = 1; *AE* = 2; and *AE* = 3. Significance testing using a chi-square test of homogeneity failed to provide conclusive evidence of an association between *AE* scores and demographic characteristics. An ordinal regression analysis also failed to detect a significant association. In addition, a cluster analysis was conducted to explore the demographic description of these groups. The results of the cluster analysis were not meaningful. The following sub-sections present the results of: (a) significance tests; (b) ordinal regression; and (c) cluster analysis related to this question.

4.5.1 Significance testing of demographic variables on *AE* scores.

Gender. A chi-square test of homogeneity showed that there was a significant difference in affect group compositions of males and females (Pearson chi-square = 17.586, p = 0.004) (Figure 4.8). However, pairwise comparisons showed that the gender compositions of the six *AE* groups were similar in most pairs (Table 4.2). Only two out of 15 comparisons were statistically significant. Therefore, it is concluded that any particular male or female was not likely to demonstrate a tendency towards a particular *AE* score at a rate greater than by chance.

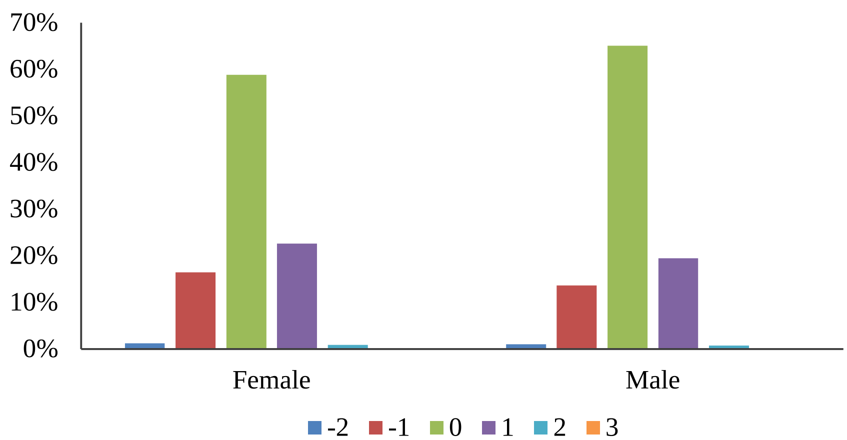

Figure 4.8. AE group composition of male and female.

Table 4.2

Pairwise Comparison of Gender Composition

	AE = -2	*AE* = -1	*AE* = 0	*AE* = 1	*AE* = 2
AE = -1	0.002				
AE = 0	0.948	9.444**			
AE = 1	0.026	0.114	9.261**		
AE = 2	0.012	0.010	0.485	0.000	
AE =3	2.063	2.121	1.595	2.046	1.939

**$p < 0.01$.

Age. A chi-square test of homogeneity showed that the *AE* group compositions were similar among the five age groups (Pearson chi-square = 24.169, p = 0.235) (Figure 4.9). The pairwise comparisons showed that the age compositions of the six *AE* groups are similar in most pairs (Table 4.3). Only one out of 15 comparisons were statistically significant. Therefore, it was concluded that any particular age group was not likely to demonstrate a tendency towards a particular *AE* score.

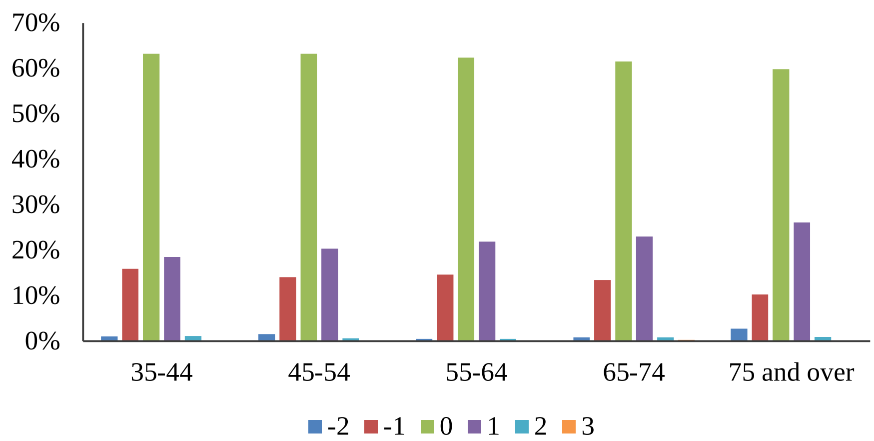

Figure 4.9. AE group composition of the six age groups.

Table 4.3

Pairwise Comparison of Age Composition

	AE = -2	*AE* = -1	*AE* = 0	*AE* = 1	*AE* = 2
AE = -1	10.374*				
AE = 0	8.405	2.280			
AE = 1	7.744	8.318	5.824		
AE = 2	3.342	2.205	2.761	4.158	
AE =3	2.926	3.173	2.981	2.660	2.177

*$p < 0.05$.

Marital status. A chi-square test of homogeneity showed that there was a significant difference in *AE* group compositions among the six marital status groups (Pearson chi-square = 48.051, p = 0.004) (Figure 4.10). However, pairwise comparisons showed that marital status compositions of the six *AE* groups were similar among most pairs (Table 4.4). Eleven out of 15 comparisons were not statistically significant. Therefore, it was concluded that affiliation within any particular marital status group was not likely to demonstrate a tendency towards a particular *AE* score.

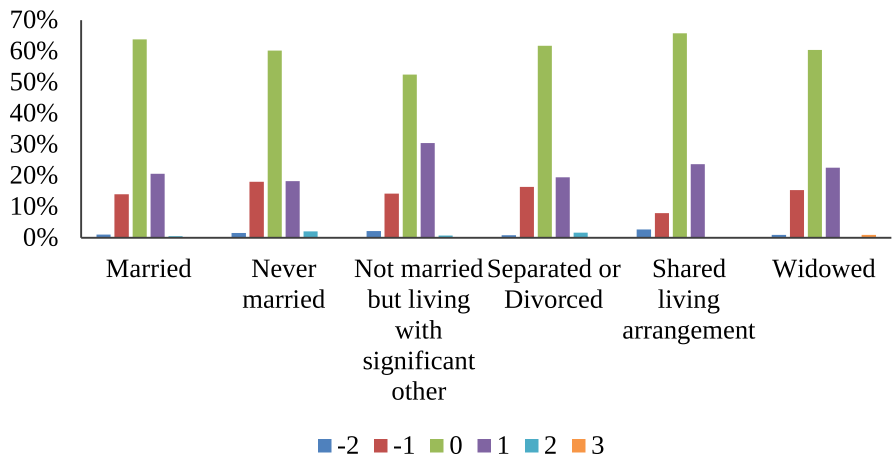

Figure 4.10. AE group composition of six marital status groups.

Table 4.4

Pairwise Comparison of Marital Status Composition

	AE = -2	*AE* = -1	*AE* = 0	*AE* = 1	*AE* = 2
AE = -1	4.278				
AE = 0	4.542	7.225			
AE = 1	2.559	9.334	10.095		
AE = 2	7.088	9.819	16.367**	17.617**	
AE =3	7.179	9.880	11.109*	9.481	12.482*

$^{*}p < 0.05$. $^{**}p < 0.01$.

Education. A chi-square test of homogeneity showed that the *AE* group compositions were significantly different among the six educational status groups (Pearson chi-square = 100.279, p = 0.000) (Figure 4.11). However, pairwise comparisons showed that educational status compositions of the six *AE* groups were only significant for approximately half of the pairs (Table 4.5). Eight out of 15 comparisons were statistically significant. It was not conclusive if any particular educational status was likely to demonstrate a tendency towards a particular *AE* score. However, among the demographic characteristics, education was one of two variables closely associated with *AE*. Specifically, those with less education were more likely to exhibit a negative affect.

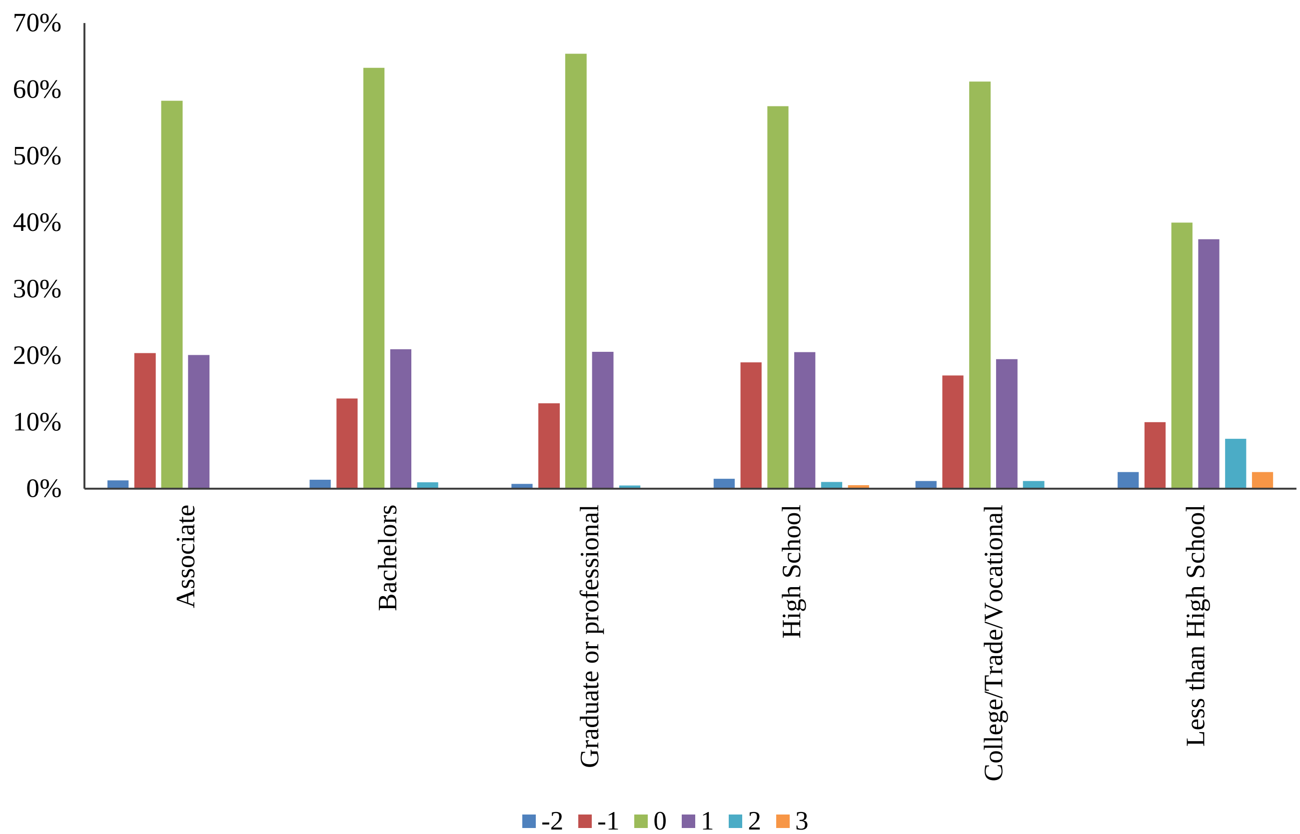

Figure 4.11. AE group composition of six educational status groups.

Table 4.5

Pairwise Comparison of Educational Status Composition.

	AE = -2	*AE* = -1	*AE* = 0	*AE* = 1	*AE* = 2
AE = -1	3.744				
AE = 0	5.602	20.131**			
AE = 1	3.108	14.501*	10.159		
AE = 2	5.088	25.589***	38.181***	14.224*	
AE =3	10.584	42.342***	54.082***	21.677**	5.757

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Household income. A chi-square test of homogeneity showed that there was a significant difference in *AE* group compositions among the five household income groups (Pearson chi-square = 84.782, p = 0.000) (Figure 4.12). The pairwise comparisons showed that the income group compositions of the six *AE* groups were different in most pairs (Table 4.6). Ten out of 15 comparisons were statistically significant. Therefore, it was concluded that income was one of two demographic characteristics that was most likely to be associated with a particular *AE* group. Results showed that the majority of respondents in each income group had *AE* = 0, which means there was no difference in their predicted *SE* score and actual *SE* score. The respondents with income more than $100,000 had the highest proportion (67%) of *AE* = 0, whereas respondents with income lower than $25,000 had the lowest proportion (56%) of *AE* = 0.

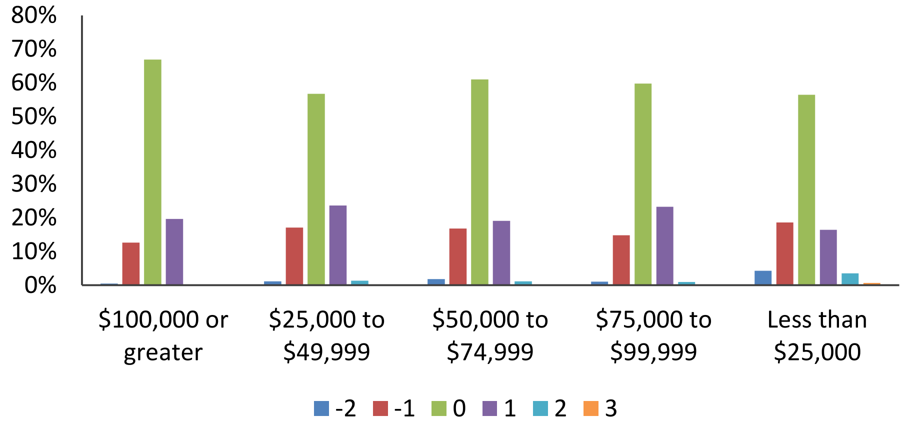

Figure 4.12. AE group composition of five income groups.

Table 4.6

Pairwise Comparison of Income Group Composition

	AE = -2	*AE* = -1	*AE* = 0	*AE* = 1	*AE* = 2
AE = -1	12.605*				
AE = 0	25.782***	18.448**			
AE = 1	24.789***	7.948	12.076		
AE = 2	1.667	14.820**	27.766***	25.126***	
AE =3	1.868	6.601	9.859*	11.074*	2.674

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

4.5.2 Ordinal Regression Analysis. An ordinal logistic regression analysis where six *AE* groups were regressed against the demographic characteristics demonstrated that although the overall model was significant (Chi-square = 3077.07, p = 0.003), the model was not a good fit. The pseudo R-square (Nagelkerke = 0.012) was particularly low. Individual parameter estimates for demographic variables also showed that 17 out of the 19 demographic dummy variables did not have a significant association with *AE* scores (Table 4.7). Only two educational status dummy variables were found to have a significant relationship with *AE* groups. When controlled for all the variables, the significance of income disappeared. This analysis showed that demographic characteristics are not a strong predictor of *AE* groups.

Table 4.7

Ordinal Regression Analysis of Demographic Characteristics

Variable	Estimate
Female	-0.052
Age 35-44	0.143
Age 45- 54	0.059
Age 55- 64	Reference
Age 65- 74	-0.075
Age over 75	-0.194
Married	Reference
Never Married	0.124
Separated/Divorced	0.042
Widowed	0.061
Living Together	-0.328
Shared Living	-0.212
Less than High School	-1.103***
High School	0.229
College	0.159
Associate Degree	0.303*
Bachelor’s Degree	0.012
Graduate	Reference
Income <25k	0.247
Income 25k - 49K	-0.068
Income 50k -74K	0.118
Income 75K - 99k	-0.082
Income >100k	Reference

*$p < 0.05$. ***$p < 0.001$.

4.5.3 Cluster Analysis using *AE* scores and demographic variables. A cluster analysis based on a hierarchical technique using the Ward linkage method and squared Euclidian distance measure was conducted to derive a demographic description of the *AE* groups. The agglomeration schedule (Figure 4.13) depicts a large number of possible clusters; however, no meaningful clusters emerged. Other alternative cluster methods were also attempted with a little improvement. It was concluded that demographic factors and *AE* scores did not demonstrate a meaningful description of the sample. Therefore, the analysis proceeded to explore the relationship between actual *PR* scores with the *AE* groups, while controlling for the demographic characteristics, rather than predicting *PR* scores with clusters.

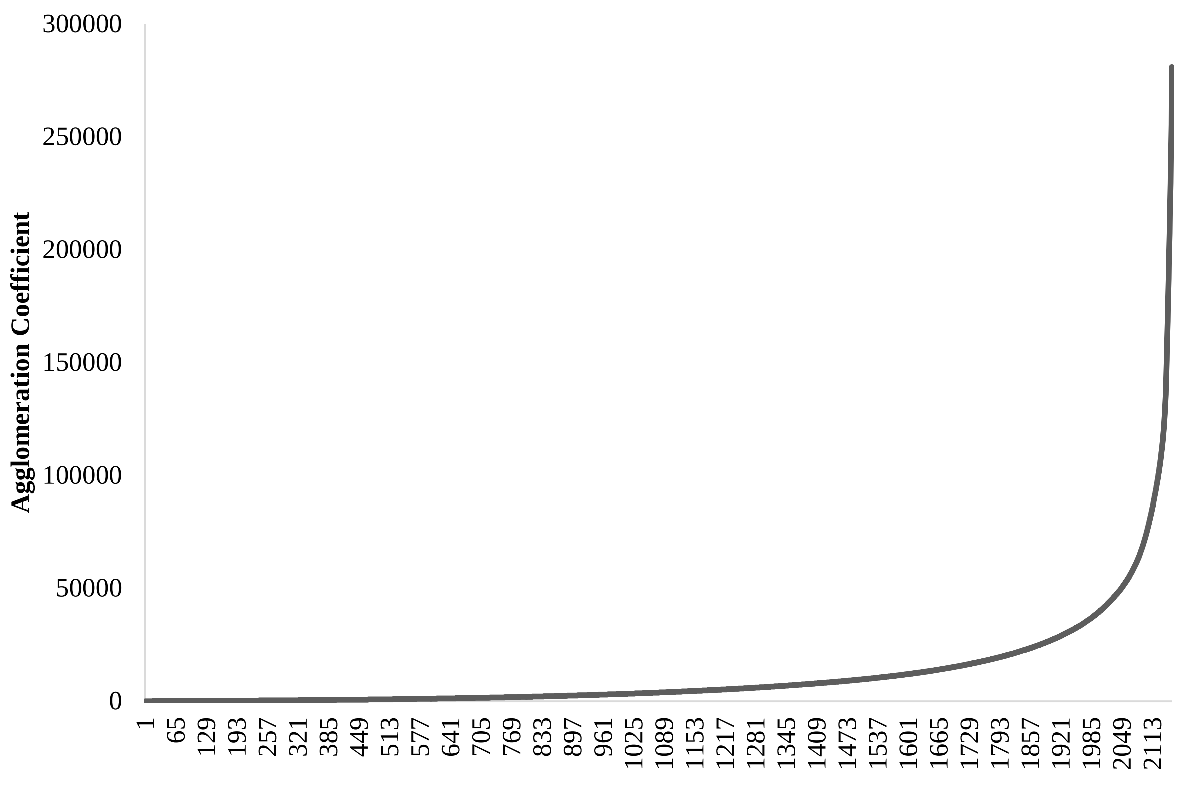

Figure 4.13. Agglomeration schedule of hierarchical clustering.

4.6 Association of *AE* Groups and *PR* Scores

The fifth and final research question of the study asked if there was an association among *AE* groups and investors' *PR* scores. The association of *AE* groups with *PR* scores was explored using Analysis of Variance (ANOVA) and Ordinary Least Square (OLS) regression techniques. Figure 4.14 shows the average *PR* scores of the different *AE* groups. The ANOVA showed that there was a significant relationship between *AE* groups and *PR* scores (F = 14.639, p = 0.000). However, this analysis was conducted without controlling for the demographic characteristics of the respondents. Hence, a further ordinary least square regression analysis was conducted using demographic characteristics as control variables. The analysis also included the reliance on a professional advice variable to control for financial planner effects. For simplicity, three broad categories – (a) negative *AE*; (b) neutral *AE*; and (c) positive *AE* – were used in the analysis. The three positive *AE* groups were consolidated into one positive *AE* group and the two negative *AE* groups were consolidated into one negative *AE* group. Previous literature supported the use of three broad categories (see Moreschi, 2005). The *AE* group with a score of zero was used as the reference category. The overall model was significant (F = 17.240, p = 0.000). There was a significant relationship between *AE* groups and *PR* score. This result showed that after controlling for demographic characteristics and reliance on profession advice, being in a positive or negative *AE* group significantly reduced *PR* scores (Table 4.8) compared to the reference category of *AE* = 0.

There was a significant relationship between *AE* groups and *PR* scores. Those investors whose predicted *SE* matched their observed *SE* (i.e., *AE* = 0) held significantly more risky assets in their portfolios than investors whose predicted and observed *SE* did not match (a positive or negative *AE*). Female respondents had significantly lower *PR* scores than male respondents. Respondents who were 35 to 44 years of age had significantly lower *PR* scores than the reference category who were 55 to 64 years of age. No significant difference was found for the other age groups. Respondents who were widows had lower *PR* scores than the married respondents. Those respondents with a shared living status also had lower *PR* scores than married respondents. All educational status categories, but not Bachelor's degree holders, had significantly lower *PR* scores than the graduate degree holders. All income groups had significantly lower *PR* scores than respondents with income greater than $100,000. Respondents who sought professional financial advice had significantly higher *PR* scores than the respondents who did not. These findings have broader implications concerning the wealth gap often seen at the macro-economic level and for financial planning practice. Results suggest that financial planners must not only measure the *FRT* of their clients, but they also need to look at the *AE* of their clients. The next chapter discusses and lays out the mathematical process of estimating *AE* from *GL-FRT* scores.

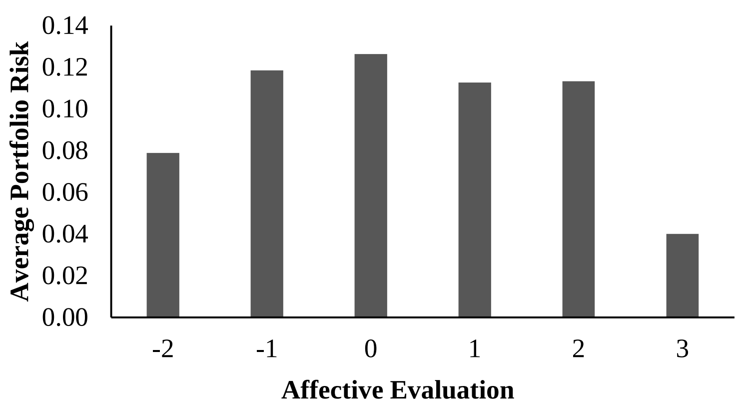

Figure 4.14. Portfolio risk (*PR*) scores of different *AE* groups.

Table 4.8

OLS Regression Analysis of AE on PR Scores

Dependent Variable: Portfolio risk	Beta	t-value
(Constant)		38.598
Negative affect	-0.044**	-2.775
Positive affect	-0.087***	-5.512
Female	-0.092***	-5.797
Age 35-44	-0.069***	-3.718
Age 45- 54	0.005	0.276
Age 65- 74	-0.019	-1.127
Age over 75	-0.001	-0.058
Never Married	-0.012	-0.752
Separated/Divorced	0.006	0.378
Widowed	-0.045**	-2.820
Living Together	-0.019	-1.235
Shared Living	-0.038*	-2.504
Less than High School	-0.033*	-2.118
High School	-0.070***	-4.355
College	-0.048**	-2.786
Associate Degree	-0.070***	-4.232
Bachelor's Degree	-0.002	-0.113
Income <25k	-0.121***	-7.547
Income 25k - 49K	-0.134***	-7.629
Income 50k -74K	-0.081***	-4.757
Income 75K - 99k	-0.053**	-3.210
Professional Advice	0.084***	5.438

*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

4.7 Summary

This chapter started with two exploratory factor analyses findings of the *GL-FRT* questionnaire to explore to what extent people exhibit affect during the evaluation of *FRT* as suggested by the RaF hypothesis. The result of the first factor analysis of all 13-items showed that there were two components to *FRT*. One component was composed mainly of nine objective assessment items that were the indicators of *OE* of *FRT*. After further analysis, eight items were combined into an *OE* scale. One item was chosen as an indicator of *SE*. A differential prediction model using an ordinal regression demonstrated that respondents did exhibit *AE* as suggested by the RaF hypothesis. This model was used as a methodology to estimate *AE*.

A series of statistical analyses using chi-square tests of homogeneity of demographic characteristics for each *AE* group, an ordinal regression analysis of demographic characteristics as a predictor of *AE* groups, and a cluster analysis using *AE* groups and demographic characteristics showed that demographic characteristics were not good descriptors of *AE* groups. Finally, the chapter reported the findings of an OLS regression analysis of *AE* groups and *PR* scores controlling for the demographic variables and reliance on professional advice. In this analysis, each respondent's *PR* score was the dependent variable, *AE* groups were the independent variables, and demographic characteristics and reliance on professional advice were control variables. *AE* groups were found to be associated with *PR* scores. The following chapter discusses these findings in the light of the theoretical foundations used in this study and previous literature. Chapter Five also describes how these findings can effectively be incorporated into the practice of financial planning.

CHAPTER 5

DISCUSSION, IMPLICATIONS, RECOMMENDATIONS, AND CONCLUSIONS

5.1 Overview of the Study

This chapter discusses the results of the study that developed and empirically tested a model using data from the Rutgers New Jersey Agricultural Experiment Station Investor Risk Tolerance database. The purpose of this study was to develop a methodology to estimate affect (i.e., feelings), use affect to describe investors, and to determine the degree to which the affect measure is associated with investor's portfolio risk. A model was developed to estimate affect (i.e., *AE*) based on the Risk-as-Feelings (RaF) hypothesis and Classical Test Theory (CTT). The model was empirically tested for differences in demographic characteristics, such as gender, age, marital status, education, and income. The respondents were then grouped based on the similarity in their *AE* scores. To determine the significance of these groups, the association between investment behavior and *AE* groups was empirically tested. This chapter begins with a discussion of two elements of *FRT* evaluation: *OE* and *SE*. This discussion is followed by a description of *AE* scores and their association with the portfolio risk undertaken by the respondents. The chapter closes with recommendations, a description of a tool for financial planners, limitations, and future research directions.

5.2. Discussion

This chapter presents an interpretation of findings of the five specific research questions addresses in this study. The first and second research questions were related to how *SE* and *OE* could be measured so that these measures could be used in an *AE* estimation. These questions were addressed by two Exploratory Factor Analysis (*EFA*) tests using *GL-FRT* data. These *EFA*s identified items used in measuring *SE* and *OE*. This study used the 13-item *GL-FRT* scale developed by Grable and Lytton (1999). This measure was particularly chosen because the survey was (a) available in the public domain, (b) easy to administer, and (c) relatively easy for respondents to answer (Gilliam et al., 2010a). The results of the preliminary *EFA* showed that there were two components in the *GL-FRT* scale. Multi-dimensionality of *FRT* is a crucial criterion for a scale (Callan & Johnson, 2002). The results also indicated that one component contained mainly those items that represented cognitive assessments. The other component contained subjective assessments.

The study further explored if it was possible to develop an instrument based only on the cognitive assessments to measure *OE*. According to Loewenstein et al. (2001), cognitive assessment means an evaluation of severity and probability of the outcome of choice alternatives through some calculation based on expectation and arriving at a decision. The definition suggests that a cognitive assessment has three main elements: (a) probability of the outcome, (b) choice alternatives, and (c) expectation based calculation. There were 9 cognitive assessment items in the *GL-FRT* scale that met these criteria. An example of a cognitive item is Item 2 of the *GL-FRT* scale that asked, “You are on a TV game show and can choose one of the following. Which would you take? (1) $1,000 in cash; (2) A 50% chance at winning $5,000; (3) A 25% chance at winning $10,000; or (4) A 5% chance at winning $100,000.” This item meets the three criteria outlined by Loewenstein et al.; the probable chance of winning $100,000 is less than any of the other options; however, in terms of an expectation based calculation, the payout of $5,000 ($100,000 x 5%) is greater than the payout offered in the other answers. As a result, a respondent who chooses the riskiest choice is considered to have a higher risk tolerance compared to someone who chooses another answer (Grable & Lytton, 1999). There is an alternative to cognitive assessments to measure *OE*. For example, Schooley and Worden (1996) used asset allocation as a measure of objective risk-tolerance. Using this method, an investor whose investment portfolio has more equities would be assumed to have a higher risk-tolerance. On the other hand, an investor who holds their investment in fixed income assets would be assumed to have a lower risk-tolerance. However, risk tolerance via asset holdings may pose validity problems. For example, asset allocation based measures assume that investors act in a rational way and that a person's asset allocation is a result of personal choice rather than the advice of a third party (Grable & Lytton, 1999). Elvekrog (1996) and Train (1995) observed that asset allocation based 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 investor behavior. Therefore, measuring *OE* with cognitive assessment methods is likely to be more valid than an asset allocation method. *OE* scores, based on 8 cognitive assessment items, also meets other psychometric criteria (MacCrimmon & Wehrung, 1986): (a) some central concept of risk, (b) allowance for the derivation of a risk measure, (c) relevance to respondents, and (d) ease of administration. In summary, the findings of the current study and previous literature suggest that the cognitive assessment items can be used to measure *OE*.

Validity and reliability play a significant role in the development of an instrument. Many researchers have also stressed the importance of validity and reliability in the development of *FRT* assessment instruments (MacCrimmon & Wehrung, 1986; Roszkowski et al., 1993; Roszkowski, 1995). Grable and Lytton (1999) suggested that future instruments designed to measure risk-tolerance should have reasonable level of reliability with a high criterion-related validity. Validity plays a critical role in the creation of instruments designed specifically to predict and measure behavioral attitudes (Babbie, 2013). An *FRT* instrument should have face validity, convergent validity, and internal validity (Grable & Lytton, 1999). Grable and Lytton suggested that a review of previous literature and empirical observation are two methods that can be used to test face validity. In the current study, the face validity of the *OE* scale was assured theoretically by combining, modifying, and integrating widely used *GL-FRT* items and empirically through factor analysis. Convergent validity was tested by comparing different measures of cognitive assessment, and it was found that these measures were correlated significantly and substantially with one another. Internal validity of the *OE* scale was tested by comparing the scores from this scale with that of *PR* scores. This hypothesis was based on the Modern Portfolio Theory (Markowitz, 1952), which predicts that higher risk tolerance results in greater equity ownership. The respondents with a higher proportion of equities have higher *PR* scores. The results showed a significant positive association between *OE* scores, as measured by 8 items, and *PR* scores. Reliability refers to the extent to which assessments are consistent; it is commonly assessed using Cronbach’s alpha. Grable and Lytton (1999) also stressed the importance of reliability of an *FRT* instrument with Cronbach alphas in the range of 0.5 to 0.8. The Cronbach alpha for *OE* scale (0.71) in this study was within this range. Therefore, an instrument based on the 8 cognitive assessment items was deemed valid and reliable as a scale for measuring *OE* scores.

The second component of the primary *EFA* using the 13-item *GL-FRT* contained mainly the items that represent subjective assessments. There were four such items. In this study, one item was used for measuring *SE*. This item asked, “In general, how would your best friend describe you as a risk taker? (a) A real gambler, (b) Willing to take risks after adequate research,

(c) Cautious, and (d) A real risk avoider." This particular item was chosen over other items because this item has been used in literature to assess subjective risk tolerance (Grable et al., 2009a; Grable & Roszkowski, 2007). Grable and Roszkowski (2007) used this item to measure self-assessment and found that almost 8% of respondents saw themselves as real gamblers (7.81%). The majority (52.58%) viewed themselves as being willing to take risks after completing adequate research, 32.6% indicated that they were cautious, and 7% saw themselves as risk avoiders. The distributions in Grable and Roszkowski were similar to this study with the majority (55%) viewing themselves as being willing to take risks after completing adequate research and approximately 36% of the respondents indicating that they were cautious. Of the respondents, 5% indicated that they were risk avoiders, with 4% viewing themselves as real gamblers. Moreschi (2005) and Hallahan et al. (2004) also used a single item to assess a respondent self-assessed risk tolerance. It was the last of the twenty-five questions that asked the respondent to guess his/her risk-tolerance score, before seeing the calculated score. Gilliam and Grable (2010) also used a single item to measure subjective risk tolerance. They used the following Survey of Consumer Finance risk question: "Which of the following statements on this page comes closest to the amount of financial risk that you are willing to take when you save or make investments? (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 returns; and (4) Not willing to take any financial risk." Based on this historical precedence, the single item used in this study for measuring *SE* was deemed to have sufficient face validity.

The third research question in the study asked how *AE*, a measure of affect, could be estimated from *OE* and *SE*. In the process of answering this question, the study developed a model to estimate *AE* based on a differential prediction technique using an ordinal regression analysis. The result showed that *OE* scores ranging from 8 to 25 were more useful in explaining *SE*. This finding suggests that, if a respondent's *OE* score lies between 8 and 25, the model is more likely to predict *SE* accurately. Previously, this technique was used by several researchers to predict *SE* (Gilliam & Grable, 2010; Grable et al. 2009a). The usual approach was to employ a questionnaire or survey to study the ability of individuals to forecast accurately their risk-tolerance score. In addition to calculating a risk-tolerance score, the respondents of these studies were asked to guess their risk-tolerance. The current analysis is quite similar in that respect; however, the interpretation of *RTEE* is different in the current study. In the previous studies, the *RTEE* indicated the degree to which a respondent overestimated, underestimated, or accurately estimated risk tolerance. In the current study, the *RTEE* was assumed to resemble the affect associated with risk-tolerance estimation. In this study, the analysis went one step further by estimating probability associated with this prediction. Now, financial planners can not only predict *SE* of a client but also can predict the probability of accuracy of their estimate. This ability will give an extra layer of confidence in discussing a client's *SE*. In addition, as they can confidently assess a client's *SE*, they can then proceed to measure a client's *AE* or affect more precisely.

The differential prediction modeling approach used here showed that it is possible to measure *RTEE,* which is a proxy for *AE*. From this model, it is also possible to estimate the probability of correctly predicting someone's *SE*. *AE* is the difference between a respondent's *SE* and predicted *SE* based on *OE*. This difference also represents a respondent's ability to balance the analytical system and the experiential system. When there is no difference, this indicates both of their systems are balanced. When, there is a difference, this indicates that the systems are not in balance. The imbalance may be manifested as either a positive *AE* or negative *AE*. A positive *AE* represents an underestimation of *FRT*; whereas a negative *AE* represent an overestimation of *FRT*. The results also showed that the majority (60%) of respondents were balanced in the experiential and analytical system. The other respondents were evenly split between demonstrating a positive or negative *AE*. The previous literature that studied *RTEE* showed quite different results. Moreschi (2005), employing a FinaMetrica data, reported that 4.1% were accurate in forecasting their risk-tolerance score, whereas, 22.6% overestimated and 73.3% underestimated. In the Moreschi's model, *RTEE* was calculated as (RTS-SRTS), where, RTS was the risk-tolerance score based on 24 question and SRTS was based on a single item. He did not use a differential prediction model. The RTS in his study ranged from 0 to 100. The SRTS was based on the last of the twenty-five questions that asked the respondent to guess his/her risk-tolerance score in the range from 0 to 100, before seeing the calculated score. This model was different from the approach used in the current study. The potential problem associated with Moreschi's method is that it is not possible to differentiate if the *RTEE* is indicating an affective process or a cognitive process. The differential prediction technique, on the other hand, uses predicted *SE* based on *OE* (a cognitive assessment); therefore, the *RTEE* calculated using this predicted *SE* reflects only the affective process.

Grable and Roszkowski (2007) used a differential prediction model to study the *RTEE* of women and men using 12 items from *GL-FRT* to measure risk tolerance and 1 item from *GL-FRT* to measure self-assessment. They estimated *RTEE* by calculating *SE* minus the predicted *SE*. A positive *RTEE* was interpreted as an overestimation, and a negative *RTEE* was interpreted as an underestimation. On the other hand, in the present study, *RTEE* was derived by calculating predicted *SE* minus *SE*. As a result, interpretation of *RTEE* was opposite to that of Grable and

Roszkowski. They used an ordinary least square regression in their differential prediction model, whereas, the present study used an ordinal regression model that is more appropriate given the ordinal nature of the dependent variable. The predicted mean score was 2.6 ± 0.4. Their study did not report how many respondents were underestimating, overestimating, or accurately estimating their risk-tolerance score. Gilliam and Grable (2010) also used a differential prediction technique for married men and women using the 13-item *GL-FRT* scale to measure risk tolerance and the Survey of Consumer Finance (SCF) risk-tolerance item for self-assessment. They used an ordered logit model in the differential prediction. *RTEE* was calculated by self-rating minus the predicted self-rating. Similar to Grable and Roszkowski (2007), their study interpreted a positive *RTEE* as an overestimation and a negative *RTEE* as an underestimation. They reported that *RTEE* scores were either -1, 0, 1, or 2. They found that the majority of respondents did a reasonably good job of estimating their risk tolerance. Grable et al. (2009a) also used a differential prediction model to determine if *RTEE* scores differed based on age. They used 12 items from *GL-FRT*. The *RTEE* scores ranged from a low of -1.70 to a high of 2.11. In the current study, *RTEE* scores were either -2, -1, 0, 1, 2, or 3.

The current study examined the extent to which an investor's subjective perception of risk tolerance (*SE*) differed from her objective assessment of risk tolerance (*OE*) and the possibility of utilizing this deviation (i.e., *RTEE*) as a proxy for affect (i.e., *AE*). The main finding was that investors' *SE* scores do differ from *OE* scores, and *RTEE* scores can be used as a proxy for *AE*. Lucey and Dowling (2005) reported that deviations from objective risk assessments occur across a broad range of activities and technologies, for example, nuclear accidents, genetically modified food, vaccinations, and X-rays. Slovic (1987) argued that there be consistency in deviations from objective assessments. Slovic also explained these deviations in the light of affect. Affect is a concept that has been developed by Slovic and advanced by Loewenstein et al. (2001) as a theory of how people assess risk. These authors have argued that people's decision-making may be guided by images and associated feelings that are induced by the decision-making process. They also found that people fear the unknown risks associated with different activities. In the context of *FRT*, these may include their fear of losing retirement funds, losing their house, unemployment, etc. These risks are viewed as unobservable, unknown, new, and delayed in their manifestation of harm. There is also evidence that affect is associated with both perceived benefit and perceived risk (Alhakami & Slovic, 1994; Finucane et al., 2000). It has been argued that if an activity is 'liked,' people tend to judge its risks as low and its benefits as high. If an activity is 'disliked' the judgments are the opposite (Finucane et al., 2000). Thus, if investors like their asset allocation, they will judge its risks as low and its benefits as high. As a result, they will indicate higher subjective risk tolerance than their objective assessment. On the other hand, if they disliked their allocation, they will indicate lower risk tolerance than their objective assessment. Similar insights were reported by MacGregor, Slovic, Dreman, and Berry (2000) who found that investors appeared to make decisions consistent with the prediction of affect; the valuation of a company's equity appeared to be influenced by whether an investor liked or disliked the company. This evidence indicates that the *RTEE* estimated as the deviation from the objective assessment is likely a useful a proxy indicator of *AE* (i.e., affect).

A series of statistical analyses (e.g., chi-square test of homogeneity, cluster analysis, and regression analysis) using the demographic characteristics of respondents answered the fourth question that asked how *AE* groups can be described based on respondents' demographic characteristics. The findings showed that the demographic characteristics of respondents were not good descriptors of *AE* groups. Chi-square tests showed that gender, age, and marital status compositions were similar among the *AE* groups. There was a 50% probability that the education status composition was different among the *AE* groups. Income composition was also likely to be different among the *AE* groups. An OLS regression analysis revealed that only a small number of demographic variables had a significant association with the *AE* groups. Gender, age, marital status, and income variables were not associated with *AE*. Only the education categories "Less than high school" and "Associate Degree" were significantly associated with *AE*.

Several previous studies focused on the identification of demographic characteristics of respondents that were significantly associated with *RTEE* (Gilliam & Grable, 2010; Grable & Roszkowski, 2007; Grable et al., 2009a; Moreschi, 2005). The findings of the previous literature on *RTEE* are different from that of the current study. Grable and Roszkowski (2007) in their study reported a significant association between *RTEE* and gender. They showed that women were more likely to underestimate their risk tolerance while men were more likely to overestimate their risk tolerance. They also reported that older respondents underestimated their risk tolerance. In their study, persons with a graduate education were more likely to overestimate their risk tolerance. There may be an econometric concern about the methodology used in their study. The main econometric concern is the use of ordinary least square regression when the dependent variable was ordinal in nature. A similar econometric issue was observed by an earlier study in Moreschi (2005) where three linear and three non-linear models were used and it was reported that men made significantly smaller *RTEE*, as did respondents with more education. They did not find conclusive evidence of associations of age and income with *RTEE*. Hawkes (1971), Morris (1970), O'Brien (1982), Reynolds (1973), Somers (1974), and Smith (1974) reported that the biases in using continuous variable methods (e.g., OLS) for ordinal variables are significant and that special techniques for ordinal variables are required. Therefore, the association between demographic variables and *RTEE* reported by Grable and Roszkowski (2007) and Moreschi (2005) may have been subject to high degree of biases. In one study, Gilliam and Grable (2010) addressed this econometric issue and used ordinal regression to determine if *RTEE* existed after controlling for a respondent's sex, age, the number of years married, and educational level. They reported that gender, age, and education were significantly associated with *RTEE*. Their model was significant with only 5% of the variance explained by the model. The small degree of variance explained by the model was similar to the current study. In another study, Grable et al. (2009a) found that younger respondents were more likely to overestimate, and older respondents were more likely to underestimate their risk tolerance. Married respondents were more likely to underestimate risk tolerance than the single respondents. The findings from the previous literature shows that there is no general consensus on the nature of association between demographic variables and *RTEE*.

In the tests of homogeneity and regression analyses, it was found that there was little conclusive evidence of an association between *AE* and demographic characteristics. As a result, it was not possible to develop clusters based on *AE* and demographic factors. In the current study, the demographic characteristics were found to be not useful in creating clusters of the respondents with varying level of *AE*. Therefore, concludes significant conclusion form this study is that demographic variables are not good descriptors of *AE* groups. This finding has significance for financial planning practice. Financial service professionals commonly use heuristic judgement about demographic characteristics to assess and predict financial risk tolerance (Roszkowski et al., 1993). A key point to be noted from the current study is that demographic characteristics do not appear to be a reliable predictor of an investor's affect associated with risk tolerance. Grable (2000) and Grable and Lytton (1998) also observed that the majority of risk-tolerance heuristics can lead to potentially serious miscalculations and incorrect categorizations of individuals into risk tolerance groups.

Finally, the study examined the relationship between *AE* groups with *PR* scores controlling for demographic variables and reliance on professional advice to answer the fourth research question that asked if investors' *PR* scores differed among the *AE* groups. Allocation of assets in an investor's portfolio involves the weighing of long-term benefits and costs, so it seems reasonable to hypothesize that feelings of investors influence their portfolio risk. Over the past two decades there has been an increase in interest in the influence of affect has on economic behavior (e.g., Loewenstein, 2000; Romer, 2000, Thaler, 2000). Loewenstein (2000) argued that the feelings experienced at the time of making a decision often propels behavior in directions that are different from that dictated by a weighing of the long-term costs and benefits of disparate actions. The current study found support for this hypothesis. The study found that portfolio risk is associated with a respondent's affect. Respondents with a neutral *AE* had higher *PR* scores than those who had a positive or negative affect, meaning people with a neutral affect (i.e., whose experiential and analytical systems were balanced) are likely to have more risky assets in their portfolio. So, the degree of affect has little significance in having lower *PR* scores. Rather, it is important that a client's affect and cognitive evaluations be balanced. If a client is balanced in her affect and cognitive evaluations, she is more likely to have risky assets in her portfolio than another client who shows imbalance in their affect and cognitive evaluations, *ceteris paribus*. For a financial planning practitioner, it is, therefore, important to notice if clients have balanced affect and cognitive evaluations. Some people may use more affect in their risk assessment; some people may use more of cognitive assessment in their risk evaluations. The findings from this study show that investors who exhibit a positive or negative affect are more likely to have lower *PR* scores, thus less risky assets in their portfolio. The key point to note is that affect may be veering consumers to choose different portfolios from what would be optimal; as a result, they may accumulate less wealth over their lifetime. Previously, researchers reported that higher risk-tolerance scores were associated with greater ownership of risky assets and negatively associated with ownership of risk-free assets (Gilliam et al., 2010a). However, the findings from this study demonstrate that after controlling for demographic characteristics and reliance on financial advisors it is the affective evaluation of *FRT* that appears to be associated with individual asset allocation.

Moreover, *PR* score were found to be associated with several demographic variables. Females had lower *PR* scores than their male counterparts. Therefore, after taking affect into account, females had less risky assets than males. The lower *PR* scores for females may help explain why women accumulate less wealth over their lifetime than men (Jianakoplos & Bernasek, 1998). Previous literature has also found that males are more likely to invest in risky financial assets than females (Zagorsky, 2005). After taking financial risk tolerance into consideration, Gilliam et al. (2010a) also found that male respondents were likely to have a greater portfolio allocation into stocks than females. *PR* scores were also associated with respondents who were younger. Respondents who were 35 to 44 years old had lower *PR* scores than the reference category who were 55 to 64 years old. This indicates that younger respondents had less risky assets than the older respondents, *ceteris paribus*. Gilliam et al. (2010a) reported a similar finding that older respondents were more likely to allocate a higher proportion of their portfolio in risky assets (e.g., stocks) compared to younger age groups. They also reported that younger respondents were more likely to hold their asset in cash than older respondents. All the older age groups had fewer assets in cash compared to the younger groups. *PR* scores were associated with being a widow and shared living status. Respondents who were widows and/or had shared living status had lower *PR* scores than the married respondents. A widow requires more stable income sources, thus, cannot generally afford to have more risky assets in their portfolio. Gilliam et al. (2010a) reported that after controlling for other demographic variables and risk tolerance, respondents who jointly held their assets with their spouse were more likely to allocate a higher proportion of their portfolio in risky assets (e.g., stocks). *PR* scores were associated with education status. Respondents with a college level of education or less were likely to have lower *PR* scores than college graduate respondents. This means that lower level of education holders were more likely to have less risky assets in their portfolio. Bachelor's and graduate degree respondents had similar *PR* scores. Previous literature also demonstrated the significance of higher education in savings and retirement planning behavior (Springstead & Wilson, 2000; Yuh & DeVaney, 1996). *PR* scores were associated with income. Respondents with income less than $100,000 had lower *PR* scores than respondents with income more than $100,000. Income may be an important criterion that dictates the level of risky assets in a portfolio. The higher income group can afford to have a more risky asset. This is an indicator of risk capacity. Previous literature also suggests that age, gender, income, and education are significantly associated with risky asset ownership. (Chaulk, Johnson, & Bulcroft., 2003; Grable & Lytton, 2003; O’Neill, Xiao, Bristow, Brenna, & Kerbel, 2000; Sung & Hanna, 1996; Wang & Hanna, 2007; Xiao, 1996; Zhong & Xiao, 1995). Younger males with high income and higher levels of education are assumed to hold risky assets (Gilliam et al., 2010a). In summary, the present study found that after taking affect and professional help seeking into account, respondents who were male, older, married, highly educated, and high-income earners were more likely to have higher more risky asset in their portfolio.

This study also found that respondents who sought professional advice had higher *PR* scores than the respondent who did not. Thus, respondents who sought professional advice were likely to have more risky assets in their portfolio. Previous literature also found a significant association between professional help and portfolio allocation in clients' portfolios. For example, Winchester, Huston, and Finke (2011) found that individuals who used a financial planner are more likely to maintain their portfolio during a recession.

5.3. Implications

The affect or feelings experienced at the moment of assessment of risk tolerance, which are often quite independent of the consequences of the assessment, can play a critical role in the eventual overall assessment of financial risk tolerance. Financial risk tolerance is a key component in investor decision-making. Consequently, understanding affect in the self-assessment of financial risk tolerance has important implications for researchers and practitioners. The divergence between the affective reaction of an investor to financial risk and a financial planner's appraisals for financial risks creates a dilemma for financial planners. On the one hand, many planners would like to be responsive to a client's own risk-tolerance assessment. On the other hand, there is a strong rationale for basing financial planning recommendations on the best scientific assessment of risk tolerance. People utilize affect (or feelings) in their judgment of tolerance for their own risk tolerance; therefore, any assessment of financial risk tolerance should be considered with caution. Without more information about a client's affective evaluation, a financial planner is likely to misjudge risk tolerance, thus, choose a sub-optimal portfolio and produce sub-optimal returns than would be dictated by their assessed risk tolerance.

This study developed a model that can be used to assess affect associated with a financial risk-tolerance scale. The application of the current model is limited to the *GL-FRT* scale. However, the procedure can be extended to other risk-tolerance scales as well. The assessment tool suggested in this study has implications for financial planners as well as to individual investors. The major take-away of this study is that financial planners and individual investors can now assess affect quantitatively with some degree of assurance. The findings from this study will help in advancing the profession's understanding of the association between affect and portfolio asset allocation decisions.

As an adviser, it is imperative for a financial planner to create awareness among clients about the factors that may influence their choice of an asset for their portfolio. This study found that the assets chosen to build a portfolio were associated with each investor's feelings and cognitive evaluation. This means that affect may lead to financial behavior that exaggerates the risk-return tradeoff. Investors whose affect and objective assessment are not balanced may have tendencies to choose investment alternatives that provide low risk and return outcomes. In particular, affect may be critical in making satisficing decisions. Satisficing behavior was defined by Simon (1983) as, "Faced with a choice situation where it is impossible to optimize, or where the computational cost of doing so seems burdensome, the decision may look for a satisfactory, rather than an optimal, alternative" (p. 243). The current study suggests that investors who have a neutral affect were more likely to have risky assets in their portfolio. On the other hand, investors who did not have a neutral affect were more likely to hold less risky assets in their portfolio. Similar findings were reported by Bechara et al. (1997) who reported that strategy and performance in a risky card game were influenced by whether or not the participants could experience emotion. Participants who could not experience emotions were more likely to follow a high-risk strategy. Participants with a normal ability to experience emotions were more likely to follow a risk-averse strategy. The present study argues that the investors who have a neutral affect use a balanced affective and objective approach when assessing risk. Thus, they assess their risk tolerance more accurately, which may allow them to assume more risk in their portfolio. It is suggested here that an investor's objective and affective assessments should be considered as two sides of a coin that helps determine an investor's portfolio risk. Therefore, financial planners should assess not only the overall financial risk tolerance, but also the affect, associated with that assessment. The following sub-section describes how affect can be measured in practice.

5.3.1 A Measurement Tool for Practitioners.

A primary outcome of this study is the development of an assessment tool for individuals and practitioners alike that incorporates a measure of affect. The steps involved for assessing affect includes the following:

1. First, use the *GL-FRT* scale to measure a client's financial risk tolerance;
2. Use the score from question 1 from the *GL-FRT* scale as a score for *SE*;
3. Sum scores from questions 2, 4, 7, 8, 11, 12, 13, and the average score from questions, 9 and 10, from the *GL-FRT* scale as a proxy for *OE*;
4. Use the *OE* score to find the respective Beta values from Table 5.1 and the value it in probability calculations shown in Step 6. For example, if the *OE* score is 8, then the Beta value is -6.772;
5. Find the Alpha values from Table 5.1 and use these as positive values in the probability calculations in Step 6;

6. Calculate the cumulative predicted probabilities with the following standard logistic model probability formula (Norušis, 2011):

   Prob (SE = 1) = 1 / (1 + $e^{(alpha(1) + beta)}$)

   Prob (SE = 1 or SE = 2) = 1 / (1 + $e^{(alpha(2) + beta)}$)

   Prob (SE = 1 or SE = 2 or SE = 3) = 1 / (1 + $e^{(alpha(3) + beta)}$)

   Prob (SE = 1 or SE = 2 or SE = 3 or SE = 4) = 1

7. Calculate the estimated probability estimates for each *SE* category using the cumulative predicted probabilities from Step 6. The probability for *SE* = 1 does not require any modifications. For the remaining *SE* scores, calculate the difference between cumulative probabilities as follows:

   Prob (SE = 2) = Prob (SE = 1 or SE = 2) - Prob (SE = 1)

   Prob (SE = 3) = Prob (SE = 1 or SE = 2 or SE = 3) - Prob (SE = 1 or SE = 2)

   Prob (SE = 4) = 1-Prob (SE = 1 or SE = 2 or SE = 3)

8. The *SE* with the highest probability from Step 7 is the $SE_{Predicted}$

9. Calculate $AE = SE_{Predicted} - SE$

Table 5.1

Ordinal Logit Coefficients

	Parameter	Coefficients
Alphas	*SE* = 1	-7.543
	SE = 2	-4.449
	SE = 3	-0.411
Betas	*OE* = 8	-6.772
	OE = 9	-6.862
	OE = 10	-6.171
	OE = 11	-5.803
	OE = 12	-5.472
	OE = 13	-5.167
	OE = 14	-4.763
	OE = 15	-4.515
	OE = 16	-4.201
	OE = 17	-3.948
	OE = 18	-3.626
	OE = 19	-3.404
	OE = 20	-2.952
	OE = 21	-2.654
	OE = 22	-2.600
	OE = 23	-2.489
	OE = 24	-1.504
	OE = 25	-1.459
	OE = 26	-0.936
	OE = 27	-1.553
	OE = 28	19.880
Reference	*OE* = 29	0.000

5.3.2 Measuring *AE* from *GL-FRT* Score: An example. A step-by-step calculation of *AE* scores using *GL-FRT* score is illustrated below:

Step 1: An investor's responses to the *GL-FRT* scale are:

Item	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13
Score	3	2	2	2	2	2	2	3	1	3	4	2	2

Step 2: *SE* = 3

Step 3: *OE* = 2 + 2 + 2 + 3 + ((1 + 3) / 2) + 4 + 2 + 2 = 19;

Step 4: For *OE* = 19.000, Beta = -3.404;

Step 5: Alpha (1) = 7.543; Alpha (2) = 4.449; and Alpha (3) = 0.411;

Step 6: Cumulative predicted probabilities

Prob (*SE* = 1) = 1/ (1 + $e^{(7.543 – 3.404)}$) = 0.016

Prob (*SE* = 1 or *SE* = 2) = 1/ (1 + $e^{(4.449 – 3.404)}$) = 0.260

Prob (*SE* = 1 or *SE* = 2 or *SE* = 3) = 1/ (1 + $e^{(0.411 – 3.404)}$) = 0.952

Prob (*SE* = 1 or *SE* = 2 or *SE* = 3 or *SE* = 4) = 1

Step 7: Estimated probability estimates for each *SE* categories

Prob (*SE* = 1) = 0.016

Prob (*SE* = 2) = 0.260 - 0.016 = 0.244

Prob (*SE* = 3) = 0.952- 0.260 = 0.692

Prob (*SE* = 4) = 1-0.952 = 0.048

Step 8: *SE* = 3 has the highest probability (0.692), therefore, the $SE_{Predicted}$ = 3;

Step 9: *AE* = 3 - 3 = 0.

5.4 Recommendations for Future Research and Limitations

Although the findings from this study are noteworthy, there are several limitations associated with the study that need to be discussed. First, the study estimated affect indirectly from each respondent's objective and subjective risk-tolerance assessment. This was an exploratory study to be used as a starting point for understanding the affect of investors. Further study should include direct assessments of affect as a way to validate some of the findings. Future studies should also look to see if it is possible to determine investment personality using affect.

Second, the respondents used in the study were not randomly selected. The data represent a convenience sample of respondents who completed a web-based survey. As a result, certain groups of the population may not have been represented in the sample. Since the survey it was a web-based, it should be assumed and expected that the respondents were more likely to be younger and more technologically proficient than might be expected in the general population. Further research is recommended to replicate this study with a larger and more diverse randomly selected samples using other modes of data collection, for example, in-person surveys, phone surveys, mail surveys, etc.

Third, the number of variables used in the analysis was limited by the questions asked on the survey. Those variables were demographic and financial in nature. Further research should include personality constructs, such as vividness, anticipatory emotion, and mood (Loewenstein et al., 2001). Johnson, Hershey, Meszaros, and Kunreuther (1993) found evidence that people are more likely to have insurance against emotionally vivid events, even if these events are not very probable. For example, vividness may be measured with, "How vividly can you imagine, after witnessing your portfolio value depleted?" Anticipatory emotions may be measured with, "Thinking about incorporating a highly risky asset gives me sweat, butterflies, cold, turned on, excited, dizzy, heartbeat." Mood may be measured with "How would you describe your general mood today?"

Fourth, the construction of the self-assessment question did not directly elicit information. The question asked how the respondent's best friend perceived the respondent rather than how the respondents viewed him/herself. There may be a difference in how a client's friends perceive a respondent's risk tolerance. A further study using a more direct self-assessment item is warranted to examine this possibility.

5.5 Conclusions

This study developed and empirically tested a model using data from the Rutgers New Jersey Agricultural Experiment Station Investor Risk Tolerance database. The purpose of this study was to develop a methodology to estimate affect (i.e., feelings), use affect to describe investors, and to determine the degree to which affect measure is associated with investor's portfolio risk. There were five research questions. A survey created by Grable and Lytton (1998) was used to estimate *SE* and *OE*. The Grable and Lytton survey also served as the source for demographic data. Two theories (RaF hypothesis and CTT) were utilized to guide the estimation of *AE* scores and development of *AE* groups. After that, *AE* groups, gender, age, marital status, education, and income were tested to determine if these demographic factors could be used to describe *AE* groups. A hierarchical cluster analysis procedure was also employed to describe the *AE* groups. These *AE* groups were then used to test differences in investment behaviors. The results showed that there were two components in *GL-FRT*. The one component was composed mainly of nine cognitive assessment items that were the indicators of *OE* of *FRT*. One item was chosen as an indicator of *SE*. A differential prediction model using an ordinal regression demonstrated that respondents did exhibit *AE* as suggested by the RaF hypothesis. This model can be used as a methodology to estimate *AE*. A series of statistical analyses using chi-square tests of homogeneity of demographic characteristics for each *AE* group, an ordinal regression analysis of demographic characteristics as a predictor of *AE* groups, and a cluster analysis using *AE* groups and demographic characteristics showed that demographic characteristics were not good descriptors of *AE* groups. Finally, the findings from an OLS regression analysis of *AE* groups and *PR* scores, controlling for the demographic variables and reliance on professional advice, showed that *AE* group membership was associated with *PR* scores. Those who exhibited affect held less of their portfolio in risky assets.

FRT is a fundamental input in determining an optimal portfolio allocation. The problem is that it is common for an investor to make errors when assessing his/her *FRT*. This study showed that this error is likely an indicator of affect and that affect is measurable using *AE*. The findings from this study provide financial planners a tool for estimating affect (i.e., *AE*). This tool is also helpful for investors who are increasingly responsible for their own investment decisions. As financial planners are responsible for understanding individual attitudinal differences to determine the appropriate portfolio for their clients, they may use these findings to assist clients make decisions that will help in wealth generation and fulfilling their financial goals.

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APPENDIX A

Grable-Lytton (*GL*) Risk-Tolerance Scale

1. 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

2. You are on a TV game show and can choose one of the following. Which would you take?

    a. $1,000 in cash

    b. A 50% chance at winning $5,000

    c. A 25% chance at winning $10,000

    d. A 5% chance at winning $100,000

3. You have just finished saving for a "once-in-a-lifetime" vacation. Three weeks before you plan to leave, you lose your job. You would:

    a. Cancel the vacation

    b. Take a much more modest vacation

c. Go as scheduled, reasoning that you need the time to prepare for a job search

d. Extend your vacation, because this might be your last chance to go first-class

4. If you unexpectedly received $20,000 to invest, what would you do?

a. Deposit it in a bank account, money market account, or an insured CD

b. Invest it in safe high quality bonds or bond mutual funds

c. Invest it in stocks or stock mutual funds

5. In terms of experience, how comfortable are you investing in stocks or stock mutual funds?

a. Not at all comfortable

b. Somewhat comfortable

c. Very comfortable

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

a. Loss

b. Uncertainty

c. Opportunity

d. Thrill

7. Some experts are predicting prices of assets such as gold, jewels, collectibles, and real estate (hard assets) to increase in value; bond prices may fall, however, experts tend to agree that government bonds are relatively safe. Most of your investment assets are now in high interest government bonds. What would you do?

a. Hold the bonds

b. Sell the bonds, put half the proceeds into money market accounts, and the other half into hard assets

c. Sell the bonds and put the total proceeds into hard assets

d. Sell the bonds, put all the money into hard assets, and borrow additional money to buy more

8. Given the best and worst case returns of the four investment choices below, which would you prefer?

a. $200 gain best case; $0 gain/loss worst case

b. $800 gain best case; $200 loss worst case

c. $2,600 gain best case; $800 loss worst case

d. $4,800 gain best case; $2,400 loss worst case

9. In addition to whatever you own, you have been given $1,000. You are now asked to choose between:

a. A sure gain of $500

b. A 50% chance to gain $1,000 and a 50% chance to gain nothing

10. In addition to whatever you own, you have been given $2,000. You are now asked to choose between:

a. A sure loss of $500

b. A 50% chance to lose $1,000 and a 50% chance to lose nothing

11. Suppose a relative left you an inheritance of $100,000, stipulating in the will that you invest ALL the money in ONE of the following choices. Which one would you select?

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

12. If you had to invest $20,000, which of the following investment choices would you find most appealing?

a. 60% in low-risk investments 30% in medium-risk investments 10% in high-risk investments

b. 30% in low-risk investments 40% in medium-risk investments 30% in high-risk investments

c. 10% in low-risk investments 40% in medium-risk investments 50% in high-risk investments

13. Your trusted friend and neighbor, an experienced geologist, is putting together a group of investors to fund an exploratory gold mining venture. The venture could pay back 50 to 100 times the investment if successful. If the mine is a bust, the entire investment is worthless. Your friend estimates the chance of success is only 20%. If you had the money, how much would you invest?

a. Nothing

b. One month's salary

c. Three month's salary

d. Six month's salary

Scoring

1. a=4; b=3; c=2; d=1

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

5. a=1; b=2; c=3

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=3

10. a=1; b=3

11. a=1; b=2; c=3; d=4

12. a=1; b=2; c=3

13. a=1; b=2; c=3; d=4

Source: Grable, J., & Lytton, R. H. (1999). Financial risk tolerance revisited: The development of a risk assessment instrument. Financial Services Review, 8, 163-181.

Key: Score risk tolerance Level 0-18 Low tolerance for risk 19-22 Below-average tolerance for risk 23-28 Average/moderate tolerance for risk 29-32 Above-average tolerance for risk 33-47 High tolerance for risk.

APPENDIX B

Data Analysis Statistical Results Output

Table B1

Factor Analysis of GL Score (13 Questions)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3.544	27.265	27.265	3.544	27.265	27.265	2.954
2	1.251	9.619	36.884	1.251	9.619	36.884	2.753
3	1.000	7.694	44.578				
4	.875	6.732	51.310				
5	.866	6.664	57.974				
6	.811	6.240	64.214				
7	.785	6.035	70.249				
8	.730	5.619	75.868				
9	.705	5.425	81.293				
10	.685	5.269	86.562				
11	.652	5.016	91.578				
12	.600	4.618	96.196				
13	.494	3.804	100.000				

Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Table B2

Structural Matrix of Factor Analysis of GL Score (13 Questions)

	Component	
	1	2
Q1	.544	-.367
Q2	.560	-.369
Q3	.558	-.065
Q4	.216	-.810
Q5	.202	-.732
Q6	.656	-.253
Q7	.538	-.218
Q8	.509	-.487
Q9	.481	-.192
Q10	.185	-.233
Q11	.298	-.573
Q12	.482	-.659
Q13	.616	-.288

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

Table B3

Factor Analysis of Nine Items of OE

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.697	33.712	33.712	2.697	33.712	33.712
2	.968	12.103	45.815			
3	.908	11.353	57.168			
4	.798	9.975	67.142			
5	.724	9.053	76.196			
6	.687	8.587	84.782			
7	.675	8.441	93.224			
8	.542	6.776	100.000			

Extraction Method: Principal Component Analysis.

Table B4

Structural Matrix of Factor Analysis of Nine Items of OE

	Component
	1
Q2	.592
Q4	.615
Q7	.469
Q8	.623
Avg9I10	.480
Q11	.567
Q12	.691
Q13	.573

Extraction Method: Principal Component Analysis.
a. 1 components extracted.

Table B5

Reliability Test of Nine Items of OE

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.712	.715	8

Table B6

Correlation between OE and Portfolio Risk

		OE	Portfolio risk
OE	Pearson Correlation	1	.281**
	Sig. (2-tailed)		.000
	N	10805	10805
Portfolio risk	Pearson Correlation	.281**	1
	Sig. (2-tailed)	.000	
	N	10805	10810

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

Table B7

Model Fitting of Ordinal Regression Analysis of SE on OE

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1383.627			
Final	463.817	919.810	21	.000

Link function: Logit.

Table B8

Pseudo R-Square of Ordinal Regression Analysis of SE on OE

	Pseudo R-Square
Cox and Snell	.207
Nagelkerke	.241
McFadden	.119

Link function: Logit.

Table B9

Coefficients of Ordinal Regression Analysis of SE on OE

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[*SE* = 1]	-7.543	.578	170.318	1	.000	-8.676	-6.410
	[*SE* = 2]	-4.449	.572	60.493	1	.000	-5.570	-3.328
	[*SE* = 3]	-.411	.564	.530	1	.467	-1.517	.695
Location	[NEWOE=8.00]	-6.772	.675	100.790	1	.000	-8.094	-5.450
	[NEWOE=9.00]	-6.862	.669	105.335	1	.000	-8.172	-5.551
	[NEWOE=10.00]	-6.171	.621	98.714	1	.000	-7.388	-4.953
	[NEWOE=11.00]	-5.803	.606	91.706	1	.000	-6.991	-4.615
	[NEWOE=12.00]	-5.472	.590	86.064	1	.000	-6.628	-4.316
	[NEWOE=13.00]	-5.167	.587	77.527	1	.000	-6.318	-4.017
	[NEWOE=14.00]	-4.763	.581	67.313	1	.000	-5.901	-3.625
	[NEWOE=15.00]	-4.515	.580	60.507	1	.000	-5.653	-3.378
	[NEWOE=16.00]	-4.201	.578	52.747	1	.000	-5.334	-3.067
	[NEWOE=17.00]	-3.948	.579	46.573	1	.000	-5.082	-2.814
	[NEWOE=18.00]	-3.626	.579	39.220	1	.000	-4.760	-2.491
	[NEWOE=19.00]	-3.404	.580	34.428	1	.000	-4.541	-2.267
	[NEWOE=20.00]	-2.952	.584	25.549	1	.000	-4.096	-1.807
	[NEWOE=21.00]	-2.654	.591	20.140	1	.000	-3.814	-1.495
	[NEWOE=22.00]	-2.600	.604	18.554	1	.000	-3.783	-1.417
	[NEWOE=23.00]	-2.489	.619	16.172	1	.000	-3.701	-1.276
	[NEWOE=24.00]	-1.504	.645	5.436	1	.020	-2.768	-.240
	[NEWOE=25.00]	-1.459	.691	4.455	1	.035	-2.814	-.104
	[NEWOE=26.00]	-.936	.748	1.567	1	.211	-2.402	.530
	[NEWOE=27.00]	-1.553	1.125	1.908	1	.167	-3.757	.651
	[NEWOE=28.00]	19.880	.000	.	1	.	19.880	19.880
	[NEWOE=29.00]	0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Table B10

Cross-Tabulation between AE Groups and Gender

		Gender		Total
		Male	Female	
AE	-2.00	25	18	43
	-1.00	341	242	583
	.00	1628	866	2494
	1.00	487	333	820
	2.00	19	13	32
	3.00	3	0	3
Total		2503	1472	3975

Table B11

Chi-Square Tests between AE Groups and Gender

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	17.586[a]	5	.004
Likelihood Ratio	18.510	5	.002
Linear-by-Linear Association	.009	1	.922
N of Valid Cases	3975		

a. 2 cells (16.7%) have expected count less than 5. The minimum expected count is 1.11.

Table B12

Cross-Tabulation between AE Groups and Age

		Age					Total
		35-44	45-54	55-64	65-74	Over 75	
AE	-2.00	13	18	6	3	3	43
	-1.00	197	164	163	48	11	583
	.00	781	736	694	219	64	2494
	1.00	229	237	244	82	28	820
	2.00	14	8	6	3	1	32
	3.00	1	1	0	1	0	3
Total		1235	1164	1113	356	107	3975

Table B13

Chi-Square Tests between AE Groups and Age

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	24.169[a]	20	.235
Likelihood Ratio	23.798	20	.251
Linear-by-Linear Association	5.708	1	.017
N of Valid Cases	3975		

a. 9 cells (30.0%) have expected count less than 5. The minimum expected count is .08.

Table B14

Cross-Tabulation between AE Groups and Marital Status

		Marital Status						
		Married	Never Married	Not married but living with significant other	Separated or Divorced	Shared Living Arrangement	Widowed	Total
AE	-2.00	28	6	3	4	1	1	43
	-1.00	393	69	20	81	3	17	583
	0.00	1792	231	74	305	25	67	2494
	1.00	577	70	43	96	9	25	820
	2.00	15	8	1	8	0	0	32
	3.00	2	0	0	0	0	1	3
Total		2807	384	141	494	38	111	3975

Table B15

Chi-Square Tests between AE Groups and Marital Status

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	48.051[a]	25	.004
Likelihood Ratio	38.893	25	.038
Linear-by-Linear Association	.050	1	.822
N of Valid Cases	3975		

a. 15 cells (41.7%) have expected count less than 5. The minimum expected count is .03.

Table B16

Cross-Tabulation between AE Groups and Education

		Education						
		Associate Degree	Bachelor's Degree	Graduate or Professional Degree	High School Graduate	Some College/Trade /Vocational	Some High School or less	Total
AE	-2.00	4	17	10	3	8	1	43
	-1.00	65	173	185	38	118	4	583
	0.00	186	809	944	115	424	16	2494
	1.00	64	268	297	41	135	15	820
	2.00	0	12	7	2	8	3	32
	3.00	0	0	1	1	0	1	3
Total		319	1279	1444	200	693	40	3975

Table B17

Chi-Square Tests between AE Groups and Education

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	100.279[a]	25	.000
Likelihood Ratio	60.297	25	.000
Linear-by-Linear Association	.536	1	.464
N of Valid Cases	3975		

a. 12 cells (33.3%) have expected count less than 5. The minimum expected count is .03.

Table B18

Cross-Tabulation between AE Groups and Income

		Income					Total
		less than $25,000	$25,000-49,999	$50,000-74,999	$75,000-99,999	over $100,000	
AE	-2.00	6	6	14	8	9	43
	-1.00	26	90	130	106	231	583
	0.00	79	298	472	427	1218	2494
	1.00	23	124	148	166	359	820
	2.00	5	7	9	7	4	32
	3.00	1	0	1	0	1	3
Total		140	525	774	714	1822	3975

Table B19

Chi-Square Tests between AE Groups and Income

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	84.782[a]	20	.000
Likelihood Ratio	72.353	20	.000
Linear-by-Linear Association	1.798	1	.180
N of Valid Cases	3975		

a. 8 cells (26.7%) have expected count less than 5. The minimum expected count is .11.

Table B20

Model Summary of OLS Regression Analysis of AE on PR Scores

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.296[a]	.088	.082	.0536668

a. Predictors: (Constant), Professional Advice, Positive affect, Income (<25k), Marrital_Shared Living, Educ_Assoc, Age (45-54), Marrital_Living Together, Educ_Hi Schol, Income 50k-74K, Age (>75), Female, Educ_less Hi Schl, Marrital_Never Married, Educ_College, Negative affect, Age (65-74), Income 75K-99k, Marital_Separated/Devorced, Marrital_Widowed, Educ_Bachel, Income_25-49K, Age (35-44)

Table B21

ANOVA Results of OLS Regression Analysis of AE on PR Scores

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.092	22	.050	17.240	.000[b]
Residual	11.382	3952	.003		
Total	12.475	3974			

a. Dependent Variable: Portfolio risk

b. Predictors: (Constant), Professional Advice, Positive affect, Income (<25k), Marrital_Shared Living, Educ_Assoc, Age (45-54), Marrital_Living Together, Educ_Hi Schol, Income 50k-74K, Age (>75), Female, Educ_less Hi Schl, Marrital_Never Married, Educ_College, Negative affect, Age (65-74), Income 75K-99k, Marital_Separated/Devorced, Marrital_Widowed, Educ_Bachel, Income_25-49K, Age (35-44)

Table B22

Coefficients of OLS Regression Analysis of AE on PR Scores

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.130	.003		38.598	.000
Negative affect	-.007	.002	-.044	-2.775	.006
Positive affect	-.012	.002	-.087	-5.512	.000
Female	-.011	.002	-.092	-5.797	.000
Age (35-44)	-.008	.002	-.069	-3.718	.000
Age (45-54)	.001	.002	.005	.276	.782
Age (65-74)	-.004	.003	-.019	-1.127	.260
Age (>75)	.000	.006	-.001	-.058	.954
Marrital_Never Married	-.002	.003	-.012	-.752	.452
Marrital_Separated/Devorced	.001	.003	.006	.378	.705
Marrital_Widowed	-.015	.005	-.045	-2.820	.005
Marrital_Living Together	-.006	.005	-.019	-1.235	.217
Marrital_Shared Living	-.022	.009	-.038	-2.504	.012
Educ_less Hi Schl	-.018	.009	-.033	-2.118	.034
Educ_Hi Schol	-.018	.004	-.070	-4.355	.000
Educ_College	-.007	.003	-.048	-2.786	.005
Educ_Assoc	-.014	.003	-.070	-4.232	.000
Educ_Bachel	.000	.002	-.002	-.113	.910
Income (<25k)	-.037	.005	-.121	-7.547	.000
Income_25-49K	-.022	.003	-.134	-7.629	.000
Income 50k-74K	-.012	.002	-.081	-4.757	.000
Income 75K-99k	-.008	.002	-.053	-3.210	.001
Professional Advice	.012	.002	.084	5.438	.000

a. Dependent Variable: Portfolio risk