riskTRACK

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RiskTRACK: The Five Factor Model for Measuring Risk Tolerance

Abstract

Currently, few academics agree on a standard and scientific way to measure risk tolerance. However, this study uses factor analysis and regression analysis to create a model for measuring risk tolerance. Our model, risk<u>TRACK,</u> includes the five significant factors identified for measuring risk tolerance: a <u>T</u>raditional risk factor, a <u>R</u>eflective risk factor, an <u>A</u>llocation risk factor, a <u>C</u>apacity risk factor, and a <u>K</u>nowledge risk factor. The results have obvious uses for future research streams devoted to risk tolerance and risk management.

1. Introduction

In light of recent volatility in financial markets and investor confidence in those financial markets, it has become increasingly imperative for financial advisors to understand their clients' risk tolerance. Risk tolerance is generally thought of as the level of financial risk that a client is willing to accept. However, the specifics of gauging risk tolerance have proven more complicated than this general definition implies.

Although the financial and actuarial literature is rich with studies addressing measures of risk, there are very few academic papers devoted to empirically measuring risk tolerance. Our paper focuses on measuring risk tolerance in an effort to not only grow this area of research, but also to help financial planners better understand the needs of their clients. Cordell (2001) states that "few planners understand the basic issues involved in risk tolerance assessment." This assertion seems even more valid after the 2007-2009 economic crisis and the growing frustration and disconnection between investors and their advisors. For example, Spectrem Group (2008) began looking at the impact of the 2007-2009 economic crisis by conducting focus groups based solely on affluent individuals. Spectrem Group states that affluent Americans (worth at least $1 million) became increasingly more disenchanted with their financial advisors as their net worth dropped by 30% during the latest economic downturn. Indeed, only 36% of affluent investors feel their advisors performed well during the crisis. Furthermore, only 14% of affluent investors plan to increase the use of their advisor in the future.

One obvious reason for this disconnect seems to be that advisors do not know their clients' true risk tolerance levels. Roszkowski and Grable (2005) report a 0.41 correlation between advisors' estimates of their clients' risk tolerance levels and their actual measured risk tolerance levels. Roszkowski and Grable also noted that advisors underestimated the risk tolerance of women and overestimated the risk tolerance of men. Swift (2009) asks advisors to estimate their clients' risk tolerance prior to receiving the actual results. Swift finds that advisors' estimates of their clients' risk tolerance levels are highly inaccurate. Swift quotes Geoff Davey, a leading researcher in risk tolerance, as saying, "The advisors would have been more accurate if they had simply assumed that all clients had an average tolerance for risk. And these were experienced advisors dealing with established clients."

2. Theoretical background

Risk management is a growing area of academic research. One important area of risk management that needs better assessment and understanding is risk tolerance. By accurately assessing risk tolerance, financial advisors can properly allocate a client's portfolio and balance the client's perceived trade-off between risk and return. Also, understanding a client's risk tolerance allows the advisor to not only compare the client's risk tolerance to other clients, but also track any risk tolerance changes over the client's time horizon. Furthermore, an understanding of risk tolerance can be instrumental for identifying any mismatches between a client's psychological and financial needs (Callan and Johnson, 2002).

Finally, one of the most important reasons for advisors to understand a client's risk tolerance is because the SEC has the power to enforce the "know your client" rule, which requires advisors to make detailed assessments of a client's risk tolerance (Roszkowski and Grable, 2005). However, Cordell (2001) stresses that financial advisors should not use a "superficial" risk tolerance questionnaire simply as a means to provide legal cover in case of a lawsuit. Instead, advisors should use a valid and reliable risk tolerance model that encompasses all of the "factors" of risk tolerance. Thus, the primary objective of this paper is to develop such a model.

2.1. Defining Risk Tolerance

There are several general definitions for risk tolerance in finance literature, which focus on either an amount of volatility one can tolerate or an amount of loss one is willing to incur. For example, Callan and Johnson (2002) define risk tolerance as the level of risk that a person believes they are willing to accept. A more inclusive definition of risk tolerance is the extent to which a person chooses to risk experiencing a less favorable outcome for the chance of a more favorable outcome (Roszkowski *et al*., 2005).

However, Cordell (2001) provides a specific model for risk tolerance that goes further than the previous definitions. Cordell defines risk tolerance as a combination of four risk tolerance factors: risk propensity, risk attitude, risk capacity, and risk knowledge. In other words, Cordell defines each of these four factors as they relate to risk tolerance. Risk propensity refers to the investor's financial decisions or allocation predisposition. Risk attitude is the amount of risk one chooses to incur, while risk capacity is how much risk one can afford to incur. Lastly, risk knowledge measures how well an investor understands both risk and the risk/return tradeoff. Evidence for all four risk tolerance factors can be found in academic research. For example, both Jacobs-Lawson and Hershey (2005) and Ryack (2011) provide evidence that there is a strong correlation between knowledge and risk tolerance. Thus, the focus of our study is whether or not all four of these factors or even additional factors should be used to measure risk tolerance.

2.2. Measuring Risk Tolerance

Now that we have a preliminary definition for risk tolerance, the real challenge is finding an appropriate method for measuring risk tolerance. Hanna *et al*. (2001) list four methods for measuring risk tolerance: investment choice measures, combining investment choice measures with subjective measures, measures based on hypothetical scenarios, and measures based on actual investment behavior. The first three methods measure investor preferences, which can be obtained from respondents by using specific questions within a well-designed questionnaire format. However, the fourth method, assessing actual investment behavior, requires measuring tangible observations, which can be obtained using basic understanding of economic models.

In economics, a substitute for measuring risk tolerance is measuring risk aversion, which is the concavity of an investor's utility function. This proxy is acceptable because risk tolerance is simply the inverse of the measure of Arrow-Pratt risk aversion (Eeckhoudt *et al*., 2005). Therefore, in the absence of significant economic constraints, more risk-tolerant investors (or less risk-averse investors) will take more risk and purchase more risky portfolios as long as they receive an expected risk premium. This idea follows from the standard capital asset pricing model (CAPM), which clearly shows that risk-averse investors will only purchase risky assets if their expected returns compensate for risk by exceeding the risk-free rate (Brennan and Kraus, 1976; Barsky *et al*., 1997; Eeckhoudt *et al*., 2005).

This mathematical relationship between risk tolerance and risk aversion is important because past research has shown risk aversion to be very difficult to quantify based on actual behavior. Several methods have been proposed. Hanna *et al*. (2001) summarize results from a variety of research and report that empirical estimates of risk aversion range widely. In addition, Mehra and Prescott (1985) use U.S. equity premium data (i.e. the risk premium for investing in stocks instead of risk-free treasury bills) and find that risk aversion would have to be implausibly high in order to explain historical patterns for the U.S. equity premium. They coin this observation the "equity premium puzzle." This equity premium puzzle is not an easy riddle to solve or at least the solution is not unanimous. Numerous studies examine this phenomenon and offer over ten different explanations for the equity premium puzzle (Eeckhoudt *et al*., 2005). The sheer volume of explanations is perhaps the most telling evidence for the difficulty in not only directly measuring risk aversion but also indirectly measuring risk tolerance.

However, setting aside measures based on actual behavior, recent research shows a significant link between risk tolerance and risk aversion. Faff *et al*. (2008) compare the results of respondents' risk tolerance questionnaire scores to their respective risk aversion scores deduced from online lottery choice experiments. Unlike previous research based on actual behavior, these risk aversion results were based on hypothetical scenarios where the respondents were knowingly taking part in the experiment and were not actually gambling with their own money. The findings suggest a strong correlation between risk tolerance and risk aversion when assessing decision-making under uncertainty. This linkage between risk tolerance and risk aversion was particularly strong for female respondents and when high-stake gambles were employed. More importantly, Faff *et al*. (2008) provide evidence that a psychometrically validated questionnaire can be used to measure risk tolerance in relation to risk aversion.

2.3. Improving Risk Tolerance Questionnaires

Among the criticisms highlighted by the 2007-2009 financial crisis is the revelation that current industry risk tolerance questionnaires do not work as advertised (Levisohn, 2009). Moreover, Brinker Capital (2008) reports that three fourths of advisors feel that current client risk tolerance questionnaires are not in line with actual client reactions to economic downturns. In addition, three fourths of advisors stated "yes" when asked whether there should be a reassessment of the method for measuring clients' risk tolerance levels.

Recent research also suggests that current risk tolerance questionnaires may not be consistent with one another. For example, Yook and Everett (2003) find that the types of questions included in different questionnaires vary greatly. By administering six different risk tolerance questionnaires to MBA students, they find that the correlation among risk tolerance questionnaires ranges dramatically from 0.31 to 0.78 (0.56 mean). Furthermore, when comparing students' responses to their actual investment decisions, they find that only some of the risk tolerance questionnaires can adequately gauge risk tolerance. Thus, Faff et al. (2008) may provide evidence that questionnaires can be used to measure risk tolerance, but Yook and Everett (2003) show that current risk tolerance questionnaires have left considerable room for improvement.

One focus of this paper is to obtain a more valid and reliable model for measuring risk tolerance. Although there is very little research on risk tolerance measures, the quality of any measure depends directly on the procedure used to develop the measure. That said, most of the current risk tolerance questionnaires used by financial advisors have been developed by compliance, marketing, or technical services personnel without regard to psychometric disciplines (Swift, 2009).

Our study uses factor analysis in the framework of the multi-item approach first developed by Churchill (1979), which has worked well in producing measures for desirable psychometric properties such as risk tolerance. This approach is very useful for diminishing measurement difficulties for the following four reasons: the specificity of items can be averaged out; precise distinctions can be made about clients; reliability tends to increase; and measurement error decreases. Furthermore, Churchill's approach fits our preliminary definition of risk tolerance considering that Cordell (2001) already identifies four potential risk tolerance factors. In other words, we can compare Cordell's four factors to the risk tolerance factors we isolate using factor analysis.

3. Item Generation

The first step in Churchill's multi-item approach is to capture the domain as defined. Using Cordell (2001) as our starting point, we capture the risk tolerance domain by generating a set of items or variables that cover each of the dimensions of risk tolerance. For clarification, the "items" or "variables" we generate in our study are risk tolerance "questions." Thus, we use the terms "item," "variable," and "question" interchangeably.

Our exploratory research includes financial websites, newspaper articles, and academic journals. The goal is to find a comprehensive list of various questions with slight differences. We then refine this list to isolate specific factors that measure risk tolerance. As we predicted, we found a great deal of replication among the question types used by several publicly available risk tolerance questionnaires. In particular, most of the risk attitude question types we include in our study are based on ten publicly available risk tolerance questionnaires[1] and prior academic research (Grable and Lytton, 1999, 2003; and Ardehali *et al.*, 2005). To proxy for risk propensity, we include asset allocation questions based primarily on the Global Portfolio Allocation Scoring System (PASS) developed by Droms and Strauss (2003).

Besides the four factors identified in Cordell (2001), we made sure to include a variety of questions that tested for other potential risk tolerance factors established in academic literature.

For example, we include several questions listing demographic variables such as age, gender, educational background, and marital status (Riley and Russon, 1995; Sung and Hanna, 1996; Yook and Everett, 2003). We also use the Myers-Briggs Type Indicator (MBTI) to develop personality type questions (Filbeck *et al*., 2005; McCrae and Costa, 1989). Finally, we create other questions focused on testing for specific cognitive biases such as self-control bias (Pompian, 2006).

3.1. Controlling for the Effects of Prospect Theory

So far, the theoretical basis for the questions used to measure risk tolerance has focused exclusively on expected utility theory. Expected utility theory is based on rational choices and takes into account not only risk aversion, but also differing utilities, probabilities, and payouts. However, Kahneman and Tversky (1979 and 1984) developed an alternative model called prospect theory, which lists several critiques of expected utility theory.

One of prospect theory's critiques of expected utility theory is that investors tend to overreact to small probable outcomes and underreact to medium or large probable outcomes. Khaneman and Tversky (1979 and 1984) explain that the key to prospective behavior is not how much wealth an investor has, but rather how the investor's wealth changes compared to the investor's reference wealth. This behavior explains why many individuals gamble or buy lottery tickets but still invest their money conservatively. We specifically control for this behavior by phrasing questions using values based on the percentage of the respondent's reference amount (e.g. Suppose you received an amount equivalent to 50% of your current income…).

Moreover, our research controls for three other pervasive effects that Khaneman and Tversky (1979 and 1984) list as violations of expected utility theory. First, the reflection effect states that investors do not weigh gains (e.g. 50% of winning $1000) and losses (e.g. 50% of losing $1,000) equally. To mitigate the reflection effect, we include questions concerning both recent gains and recent losses. In addition, we randomly assign positive or negative preference ordering to our answer choices. Second, the isolation effect states that investors often disregard components that alternatives share. One example is a two-stage gamble with the following two alternatives: Alternative A has a 50% chance gamble of playing a second gamble that has a 10% chance of winning $1,000; Alternative B has a 50% chance gamble of playing a second gamble that has a 20% chance of winning $500. In this example, respondents may overlook the first gamble for each alternative because the first gambles appear to be the same. To control for the isolation effect, no questions include two-stage decisions where first-stage probabilities could be potentially ignored. Third, the certainty effect states that investors may overweigh probable outcomes. One example is overweighing a gamble with a 100% chance of winning $200 compared to a gamble with a 20% chance of winning $1,000. To negate the certainty effect, all answer choices are incrementally converted to a 5-point Likert scale (except for demographic questions and risk capacity questions that required specific answer choices).

4. Data Collection

We develop an 85-item risk tolerance questionnaire,[2] which we categorize into five predicted factors based on the four factors in Cordell (2001) and an additional personality factor. These five factors include risk attitude questions (1–48), risk propensity questions (49–55), risk personality questions (56–66), risk knowledge questions (68–70), and risk capacity questions (74–84). The 85-item risk tolerance questionnaire also includes four demographic variable questions (67, 71–73) and four dependent variable questions (82–85), which are not used in factor analysis, but are included to obtain dependent variables for multiple linear regression analysis and for future research opportunities.

4.1. Zoomerang Sample: Demographics Summary

To obtain a valid and reliable sample, we use Zoomerang,[3] which is a survey clearinghouse enabling users to access over 2.5 million respondents in its sample database with each respondent cross-checked for uniqueness. A few demographic highlights are as follows. First, the majority of the 355 respondents answer that they are at least somewhat informed about financial investments and all but 23% had at least an undergraduate degree. Second, the gender breakdown is 45% female and 55% male. Third, the vast majority of respondents are married (68%) with only 24% single, 7% divorced, and 2% widowed. Fourth, the age of the respondents range from 24 to 79 with the average respondent being about 50 years of age. Finally, the average respondent is financially responsible for approximately 1.3 dependents.

4.2. Zoomerang Sample: Risk Capacity Summary

The Zoomerang database offers an accurate representation because it is balanced with the U.S. Census (unless otherwise specified). The only necessary condition we mandate for the Zoomerang sample is that most of the respondents have some investments or risk capacity. From a risk capacity perspective, our average respondent has: (1) more than $237,000 of equity in their primary residence, an investment portfolio over $346,000, a net worth close to $527,000, an annual income of nearly $100,000, and were approximately 19 years away from retirement. Many of these numbers are skewed high because 4% of respondents have over $1,500,000 in investments while the remaining 96% of the respondents have no more than $600,000 in investments. Nonetheless, over half of the sample has more than $50,000 in investments, and only 18% of the respondents have below $10,000 in investments.

4.3. Zoomerang Sample: Dependent Variable Summary

Finally, although our dependent variable questions are used in more detail with regards to the multiple linear regression analysis in the robustness section, a few general observations can be made about our sample. First, most of the respondents report that they do not let their financial advisor make financial decisions for them. Second, the actual percentage of stock that the average respondent has in his/her investment portfolio is around 32%. Since this actual percentage reflects the average respondent's preferred percentage of stock in his/her investment portfolio, it seems even more likely that most of the respondents are involved in their own financial decisions.

5. Item Purification

For item purification calculation, an all-inclusive domain sampling model is used to estimate a client's true risk tolerance score, X_T. However, in practice, using 85 questions is not reasonable for any risk tolerance questionnaire. In fact, of the 11 risk tolerance questionnaires we use in this study (Grable's 19-item questionnaire and the 10 other publicly available risk tolerance questionnaires), the number of questions they ask range from 4 to 25 (mean 12). Besides practicality, 85 independent variables also present a multicollinearity problem, which is addressed in more detail later using multiple linear regression analysis. Since only a sample of the items can be used, the purification goal of this research is to reduce the 85 items down to a more practical number of questions (with low linear inter-item correlation). The most common purification test for reducing items is factor analysis.

5.1. Factor Analysis

Factor analysis is a statistical method based on the correlation analysis of multi-variables. This interdependence analysis has two primary applications: to reduce the number of variables and to detect the appropriately structured factors for classifying variables. In other words, we detect factors by finding a pattern of correlations within a set of observed variables.

The goal is to identify a limited number of factors that explain the majority of variance in a much larger set of variables. Variables can then be eliminated in two distinct ways. First, those variables that cross-load on more than one factor can be eliminated to increase reliability. Second, those variables that do not load highly on any specific factor can also be eliminated. Thus, we perform factor analysis on the responses we obtain from our risk tolerance questionnaire in order to isolate the factors that influence risk tolerance.

First, we use the Kaiser-Meyer-Olkin (KMO) measure to test if our Zoomerang sample size of 355 respondents is adequate. The KMO measure of sampling adequacy for this factor analysis is 0.870. This KMO measure indicates that the Zoomerang sample is definitely adequate, considering that any measure over 0.500 is sufficient for a factor analysis to proceed.

The next step in factor analysis is to generate a correlation matrix for all variables to discover how much variance each factor explains. Table 1 shows that only the first five factors are retained because they have eigenvalues greater than one. The eigenvalues represent the standardized variance associated with a particular factor. Table 1 also lists the rotation sums of squared loadings (*RSSL*) values, which detail the distribution of the variance after maximizing the variance of each factor via rotation. The *RSSL* values in Table 1 show that approximately 61% of the variance was explained by the first five factors. Table 1 also shows the rotated factor matrix for the 85 risk tolerance questions. The factor matrix is rotated for the purpose of uncovering a more meaningful pattern of factor loadings, which express the correlation of each question with each factor. Several factor loadings in Table 1 do not appear because these questions either cross-load on more than one factor or because they do not correlate highly enough with any of the five factors. Thus, only 25 of the original 85 questions are not reduced by factor analysis.

(Insert Table 1)

5.1. RiskTRACK

Consistent with previous research by Cordell (2001), Table 2 shows that the five factors loaded in a predictable fashion. Table 2 lists both our predicted factors and our confirmed factors as well as the question numbers assigned to each factor. Thus, in a similar fashion as Cordell (2001), we develop our own unique model, riskTRACK, for measuring risk tolerance. We use the acronym TRACK to collectively identify the five individual factors we find for measuring risk tolerance: Traditional risk factor, Reflective risk factor, Allocation risk factor, Capacity risk factor, and Knowledge risk factor.

(Insert Table 2)

The first and third factors in our study represent two different confirmed factors within our predicted attitude factor. The question-types for these two factors are differentiated based on the "reflective effect" of Prospect Theory (Khaneman and Tversky, 1979 and 1984). Since the majority of traditional questionnaires only include questions with hypothetical gains, we address Khaneman and Tversky's reflective effect by separating all hypothetical questions into either "traditional" questions with hypothetical gains or "reflective" questions with hypothetical losses. This difference is significant. Thus, we label the first and third factors as the Traditional risk factor and the Reflective risk factor, respectively.

The other factors are also similar to our predicted factors. For example, four asset allocation (or risk propensity) questions load exclusively on the fifth factor, which we label the Allocation risk factor. In addition, four risk capacity questions load exclusively on the second factor, which we label the Capacity risk factor. Finally, based on our results, we retain all three risk knowledge questions on the fourth factor, which we label the Knowledge risk factor. Thus, our factor analysis finds five specific factors for measuring risk tolerance.[4]

6. Robustness

To ensure that these five riskTRACK factors are robust, validity and reliability checks (in addition to factor analysis) are accessed. Churchill (1979) provides the logic to determine whether the construct is captured by the measure. Let X_T be a client's true level of risk tolerance and X_O be a client's observed level of risk tolerance. For a questionnaire to be valid, differences in X_O scores must only reflect the true risk tolerance characteristic the questionnaire seeks to measure (e.g. risk attitude or risk knowledge). This means the goal is for $X_O = X_T$. However, validity concerns arise when differences in observed scores are distorted away from their true scores. These distortions often occur for the following reasons:

- Ethical characteristics (e.g. a person's willingness to answer questions honestly)
- Transient personal factors (e.g. a person's mood or state of fatigue)
- Situational factors (e.g. survey taken in workplace environment or at home online)
- Variations in administration (e.g. level of intrusiveness of survey questions)
- Sampling of items (e.g. specific wording used in questions)
- Lack of clarity of measuring instruments (e.g. vague or confusing questions that could have more than one interpretation)
- Mechanical factors (e.g. answer coding problems or calculation mistakes)

Mathematically, the full relationship can be expressed as:

$$X_O = X_T + X_S + X_R \qquad (1)$$

where X_S = systematic sources of errors (e.g. stable characteristics that affect risk tolerance) and X_R = random sources of errors (e.g. transient personal factors that affect risk tolerance). In addition to validity, we also seek a measure that is reliable. A perfectly reliable measure requires $X_R = 0$. Thus, in psychometric terms, a "valid" risk tolerance measure actually measures risk tolerance whereas a "reliable" risk tolerance measure does so with consistent accuracy (Roszkowski, Davey, and Grable, 2005).

6.1. Validity Assessment of the Dependent Variable

Multiple linear regression analysis is used to assess the validity of using our risk tolerance measure based on the five riskTRACK factors found in our factor analysis. However, linear regression analysis requires a dependent variable. Several studies have focused on calculating risk tolerance based on the proportion of wealth to risky assets (Friend and Blume, 1974; Lease *et al.,* 1974; Cohn *et al*., 1975; Siegal and Hoban, 1982; Riley and Chow, 1992). Specifically, Schooley and Worden (1996) show that the ratio of risky assets to wealth can be used as a measure of risk tolerance. Moreover, their results reveal that most individuals understand the relative level of riskiness in their investment portfolios. Therefore, consistent with prior research, we use the actual stock percentage in the respondent's investment portfolio as the dependent variable to proxy for risk tolerance, which is another important reason why risk capacity was a necessary condition for our Zoomerang sample.

To test the validity of using stock percentage as the ratio of risky assets to wealth, the following two alternative dependent variables (X_{A1} and X_{A2}) are used:

$$X_{A1} = (X_T - V_P) / V_W \quad (2)$$

$$X_{A2} = X_T \; / V_W \quad (3)$$

where X_T is the percentage of stock in the investor's portfolio, V_P is the value of the investor's portfolio, and V_W is the value of the investor's net wealth. In both cases, similar but slightly less significant results are found compared to the results using the original dependent variable (X_T).

Finally, Ardehali *et al*. (2005) point out two key assumptions for using stock percentage as a dependent variable. The first assumption is that the investor's asset allocation is his/her own choice rather than the result of a third party's decision. The second assumption is that the investor is completely aware of and in agreement with the risk in his/her investment portfolio (i.e. the investor's actual investments match his/her risk preferences). To compensate for these two assumptions, the following two questions are asked:

A. Which of the following best describes how you make your investment choices?

B. What is the percentage of stocks that you would *prefer* to have in your investment portfolio?

We control for the two key assumptions using the answers to these two questions. First, we eliminate those respondents from Question A who chose that their financial advisor made their financial decisions for them. Second, we use the respondents' answers to Question B as the new dependent variable. The results are similar to the original multiple linear regression model that did not control for either assumption.

6.2. Validity Assessment of the Independent Variables

Similar to Alli *et al*. (1993), we assess the validity of using the five riskTRACK factors found in our factor analysis as independent variables for risk tolerance by performing multiple linear regression analysis. As explained in the section above, we used the actual stock percentage in the respondent's investment portfolio as the dependent variable (X_T) to proxy for risk tolerance. We then formulate the risk tolerance regression equation below by summing the five predetermined factors: F_1 = Traditional risk factor; F_2 = Capacity risk factor; F_3 = Reflective risk factor; F_4 = Knowledge risk factor; and F_5 = Allocation risk factor.

$$X_T = c + w_1F_1 + w_2F_2 + w_3F_3 + w_4F_4 + w_5F_5 + \varepsilon \qquad (4)$$

where c is simply a constant. The weighted factors are known as factor scores (Fi), which are based on the communality of variables. A variable's communality is the amount of the variable's variance that is accounted for by the factor (Warner, 2007). More specifically, the factor scores are constructed by applying β_{vi} factor score coefficients (i.e. the loadings for each variable v on factor i shown in Table 3) to the respondent's standardized z_v scores as shown in the following equation:

$$F_i = \beta_{1i}z_1 + \beta_{2i}z_2 + \beta_{3i}z_3 + \ldots + \beta_{pi}z_p \qquad (5)$$

Finally, to test whether or not these five factors have a significant effect on risk tolerance, multiple linear regression analysis is performed to test the following null hypothesis:

$$\text{Ho: } w_1 = w_2 = w_3 = w_4 = w_5 = 0 \qquad (6)$$

Table 3 shows a stepwise linear regression for five different risk tolerance models. Both the higher adjusted R^2 and the significance of the F-test for model (5) clearly show that this model conveys more information than any of the models with less than all five factors. In fact, each factor in model (5) is significant at the 0.001 level. Moreover, the positive coefficient for each of the five factors reflects that the respondents with more risk tolerant answers had a higher ratio of risky assets to wealth. For example, those respondents with higher risk capacity or risk knowledge values had a higher percentage of stock in their investment portfolio. These results using factor scores clearly reject the null hypothesis and support the factor analysis findings that all five factors can be used to measure risk tolerance.

(Insert Table 3)

However, there has been some research that suggests unit-weighted factors are not only mathematically simpler to calculate than factor scores, but also more reliable (Warner, 2007). Thus, as a robustness check, we also perform a multiple linear regression analysis using unit-weighted factors. For the sake of brevity, our unit-weighted factor results are not included. However, the unit-weighted factor results are similar to the results in Table 3 that are based on factor scores, and both results clearly reject the null hypothesis.

As a further robustness check, we also measure the strength of the linear dependence between the five factors by calculating the Pearson correlation coefficients for the five factors. The correlation coefficients are calculated by dividing the covariance of two factors by the product of those two factors' standard deviations. We did find some significant correlation between the five variables. However, the highest degree of correlation is 0.501 between factor one and factor four. Thus, the five factors have high linear dependence.

Finally, to ensure that there is no multicollinearity problem, we calculate the variance inflation factor (VIF) for each unit-weighted factor. VIF is defined as the inverse of Tolerance (VIF = 1/Tolerance = 1/1-R^2) where a value of 5 or greater indicates a multicollinearity problem (O'Brien, 2007). The VIF values for the five factors range from 1.099 for factor three to 1.564 for factor four. These results indicate that there is no multicollinearity problem.

6.3. Reliability Assessment

Segars (1997) notes that "coefficient alpha is perhaps the most widely used metric for gauging the reliability of scale items." Also known as Cronbach's alpha, coefficient alpha measures how well a set of items measures one specific unidimensional latent construct or factor. Cronbach (1951) defines coefficient alpha as a function of the number of test items (*N*) and the average inter-correlation among the items:

$$\propto = \frac{\bar{c} \cdot N}{[\bar{v} + \bar{c} \cdot (N - 1)]} \tag{7}$$

where $\bar{v}$ is the average variance among the items and $\bar{c}$ is the average inter-item covariance. The goal is to make sure that the coefficient alpha is not less than 0.700, which would indicate poor scale reliability (Cronbach, 1951). In other words, a low coefficient alpha suggests that the set of items performs poorly in capturing the factor which motivated the measure (Churchill, 1979).

The following coefficient alphas were obtained for factors one through five respectively: 0.9025, 0.8677, 0.7786, 0.7875, and 0.5666. The coefficient alphas for the first four factors indicate high scale reliability. Although the 0.5666 coefficient alpha for the fifth factor does not suggest high scale reliability, it does suggest some reliability. This lower reliability of the fifth factor suggests either a lower reliability for risk propensity questions in general or that the specific asset allocation questions we used were not a perfect proxy for propensity questions. Although we decided to retain this factor, future studies should retest this factor's reliability.

One final method of increasing the coefficient alpha is to perform an item-by-item analysis to determine if the coefficient alpha could be improved by deleting a specific item. Our analysis finds that none of the coefficient alphas could be increased by deleting a question from any of the five factor sets. Thus, coefficient alpha provides five reliable factors including four factors with high scale reliability.

We also include three other reliability tests. First, we check for reliability by correcting for heterosckedasticity using the White procedure. Second, we perform a Hausman test and find no omitted variable bias in our regression. Third, to account for errors caused by differences in testing situation and other previously mentioned external factors, we include an iteration process to confirm that the risk tolerance construct is more than a measurement artifact (Churchill, 1979). For this final reliability check, we separate are data into two iterations. More specifically, we collect data from 200 of our 355 Zoomerang respondents at the beginning of January 2009. We then collect data from the other 155 respondents a month later. The factor analysis and robustness results for both iterations are similar to the overall findings. The findings from all three robustness checks suggest that our risk tolerance measure is reliable.

7. Summary

The goal of the research is to identify the factors needed to create a reliable and valid model for measuring risk tolerance. The risk tolerance model we formulate is based on the sum of five weighted factors: F_1 = Traditional risk factor; F_2 = Capacity risk factor; F_3 = Reflective risk factor; F_4 = Knowledge risk factor; and F_5 = Allocation risk factor. By reordering these factors, we created the acronym riskTRACK to provide a collective name for the five individual factors in our risk tolerance model.

In addition to our RiskTRACK model, our research makes contributions to the finance literature on risk tolerance and risk management. First, our riskTRACK model is the first to provide evidence for five specific factors for risk tolerance. Second, our research presents an in-depth methodology for researching other quantifiable finance measures with psychometric properties. Finally, our research presents several unique opportunities for future research.

8. Future Research Applications

Future research should definitely focus on building upon these results to test for additional risk tolerance factors that other research indicates may or may not exist. For example, one unexpected outcome from our factor analysis is the complete reduction of every personality question. This finding suggests four possible scenarios to examine with future research: (1) risk tolerance is not significantly affected by personality type, (2) using the MBTI was not the best method for testing for personality effects, (3) the questions were not developed well, or (4) many personality attributes may be indirectly measured by (or cross-correlated with) other factors. There are also numerous demographic and capacity factors that we could further explore. For example, Hallahan *et al*. (2004) find that gender, age, number of dependents, marital status, income, and wealth are all significantly related to risk tolerance. We could also build upon the work done by Hariharan *et al*. (2000) and test to see if the factors for risk tolerance change as investors near retirement.

Future research should also explore each of the five factors we identify in our study to see what makes each factor unique. For example, Brayman (2012) looks at defining and measuring risk capacity. Future studies could examine whether or not there are any underlying variables that contribute to risk capacity and whether or not all of these variables contribute to risk tolerance. Likewise, several papers like Al-Tamimi and Kalli (2009) take a deeper look at financial literacy. This research could be used to develop additional questions to test for different variables within the knowledge risk factor that we find in our study. Finally, there are several other behavioral finance theories that could be considered with regards to risk tolerance. In fact, Alghalith *et. al*. (2012) test several dominant theories in behavioral finance and find an alternative theory for prospect theory. Considering that prospect theory helped us uncover the reflective factor in our study, perhaps other theories could be used to determine additional factors.

Lastly, there are also two long-term future research applications. First, as more data is collected, changes in risk tolerance can be analyzed over time similar to Yao *et al*. (2004). This analysis may be productive in detecting how investors' attitudes towards risk change after significant events such as the 2007-2009 economic crisis. For example, Yao *et al*. (2004) find that risk tolerance tends to increase when stock returns increase and decrease when stock returns decrease. Second, with more data and research, risk tolerance could prove to be a leading variable for predicting returns or volatility in specific areas of financial markets such as fixed income, which would open up several avenues of research for comparing risk tolerance to other leading variables.

Table 1: Factor Matrix for All Risk Tolerance Questions.

In order to confirm factors for measuring risk tolerance, we perform factor analysis using 355 respondents' answers to our 85-item questionnaire. The only exceptions were the demographic questions (67, 71-73) and dependent variable questions (82-85). The factor matrix shows only those questions that load with an absolute correlation greater than 0.5 for one and only one factor. Those variables that cross-load on more than one factor are excluded. Note that all five factors below have eigenvalues greater than one. The table also lists each factor's rotation sums of squared loadings (*RSSL*) values, which explains the amount of variance attributed to each factor.

	Factor				
	1	2	3	4	5
Question 03	.695				
Question 04	.608				
Question 12	.688				
Question 13	.770				
Question 18			.795		
Question 21	.698				
Question 27			.830		
Question 29			.794		
Question 30	.791				
Question 32	.661				
Question 34	.623				
Question 37	.684				
Question 38	.753				
Question 41	.745				
Question 49					.551
Question 50					.720
Question 51					.676
Question 54					.519
Question 68				.688	
Question 69				.722	
Question 70				.683	
Question 75		.780			
Question 76		.803			
Question 77		.842			
Question 81		.748			
Eigenvalue	6.907	3.475	2.155	1.423	1.282
RSSL Variance	23.880%	11.572%	9.499%	9.031%	6.987%

Table 2: Results of Factor Analysis.

In order to confirm factors for measuring risk tolerance, we perform factor analysis using 355 respondents' answers to our 85-item questionnaire. The only exceptions were the demographic questions (67, 71-73) and dependent variable questions (82-85). The results of the factor analysis are listed in the table below including both the predicted factors and confirmed factors as well as the question numbers assigned to each factor.

Predicted Factors	Question Number	Confirmed Factors	Question Number
Risk Attitude	1 – 48	Traditional Risk Factor (F_1)	3, 4, 12, 13, 21, 30, 32, 34, 37, 38, 41
Risk Propensity	49 – 55	Capacity Risk Factor (F_2)	75, 76, 77, 81
Risk Personality	56 – 66	Reflective Risk Factor (F_3)	18, 27, 29
Risk Knowledge	68 – 70	Knowledge Risk Factor (F_4)	68, 69, 70
Risk Capacity	74 – 81	Allocation Risk Factor (F_5)	49, 50, 51, 54

Table 3: Multiple Linear Regression Model Summary Using Factor Scores.

Our factor analysis identifies the following five riskTRACK factors that measure risk tolerance: F_1 = Traditional risk factor; F_2 = Capacity risk factor; F_3 = Reflective risk factor; F_4 = Knowledge risk factor; and F_5 = Allocation risk factor. To test the validity of these five factors, multiple linear regression analysis is performed to see if the five factors measure risk tolerance. Using stock percentage as the dependent variable to proxy for risk tolerance, we develop the following regression analysis:

$$X_T = c + w_1F_1 + w_2F_2 + w_3F_3 + w_4F_4 + w_5F_5 + \varepsilon$$

where the weighted factors are calculated using their factor scores. A stepwise linear regression methodology is used to conduct F-tests for the five models. Note that significance for F-test and T-test results are denoted by (***) at the .001 level, (**) at the 0.01 level, and (*) at the 0.05 level.

	Risk Tolerance Regression Models				
Variables	(1)	(2)	(3)	(4)	(5)
c (constant)	32.434	32.434	32.434	32.434	32.434
F_1		10.092***	10.092***	10.092***	10.092***
F_2				5.589***	5.589***
F_3	10.552***	10.552***	10.552***	10.552***	10.552***
F_4			6.607***	6.607***	6.607***
F_5					4.845***
F	48.364***	52.783***	45.038***	39.633***	35.503***
Adjusted R^2	0.118	0.226	0.272	0.304	0.328

END NOTES

1. The risk tolerance questionnaires we use in this study are available at the following websites: CollegeAdvantage.com; CompassPlanning.com; FirstAmBank.com; JohnHancock.com; Kiplinger.com; MetLife.com; MoneyCentral.com; MyRiskTolerance.com; Partnervest.com; Vanguard.com.
2. We actually first perform an exploratory factor analysis using a judgment sample's responses to our original 115-item risk tolerance questionnaire. Although this exploratory factor analysis provides some additional clarity for question reduction, we use these results primarily to isolate potential factors for testing during our confirmatory factor analysis. We perform the confirmatory factor analysis using the Zoomerang sample's responses to the 85-item risk tolerance questionnaire. Since we do not detail the results of the exploratory factor analysis, we refer to confirmatory factor analysis as simply factor analysis throughout the paper.
3. All Zoomerang data and information is obtained through Zoomerang.com.
4. Note that the factors are numbered based on how they loaded during the factor analysis and are not in the same order as the riskTRACK acronym.

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