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The Complementary Nature of Financial Risk Aversion and Financial Risk Tolerance

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Abstract: Financial risk aversion and financial risk tolerance are sometimes considered to be 'opposite sides of the same coin', with the implication being that risk aversion (a term describing the unwillingness of an investor to take risks based on a probability assessment) and risk tolerance (an investor's willingness to engage in a behavior based on their subjective evaluation of the uncertainty of the outcomes) are inversely-related substitutes. The purpose of this paper is to present an alternative way of viewing these constructs. We show that risk aversion and risk tolerance act as complementary factors in models designed to describe the degree of risk observed in household investment portfolios. A series of multivariate tests were used to determine that financial risk aversion is inversely related to portfolio risk, whereas financial risk tolerance is positively associated with portfolio risk. When used in the same model, the amount of explained variance in portfolio risk was increased compared to models where one, but not the other, measure was used. Overall, financial risk tolerance exhibited the largest model effect, although financial risk aversion was also important across the models analyzed in this study.

Keywords: financial risk tolerance; financial risk aversion; risk-taking; revealed-preference; elicited-risk tolerance

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1. Introduction

Household financial decision-makers and investors make decisions in an environment characterized by uncertainty. This contrasts with managers, agents, and policymakers who generally make decisions and provide advice in systems that embody risk (Mazzoli and Marinelli 2011). While uncertainty and risk deal with situations involving the potential for positive and negative outcomes, these concepts differ in terms of the type of data available prior to engaging in a behavior (e.g., making an investment versus issuing an insurance policy) (Mowbray and Blanchard 1961). A characteristic of uncertainty is the lack of a known or calculable probability associated with the possible outcomes. While an investor, for example, may estimate outcome probabilities using their experience, judgment, or Monte Carlo simulations, the adoption of an estimation tends to be based on the investor's subjective evaluation of the situation. Risk, on the other hand, involves situations where the probability of different outcomes is known a priori or, at a minimum, can be estimated with a high degree of accuracy (e.g., the likelihood of incurring property damage associated with a storm). Stated another way, risk describes an environment with a certain level of predictability. Risks are most often quantified using statistical measurement, historical data, and probability distributions.

Before providing investment advice to clients, financial advisors are tasked, by regulators (e.g., Financial Industry Regulatory Authority (FINRA) (2023)) and the Securities and

Exchange Commission) and certification boards (e.g., Certified Financial Planner Board of Standards, Inc.), with assessing their clients' preference(s) related to engaging in risk-taking activities that entail the possibility of gains and losses. Two assessment approaches are commonly used. The first method is premised on the notion of revealed preferences. An investor's preference(s) are assumed to match their observed behavior when the choices are monetized (Arslan et al. 2020). The hypothesis underlying this assessment approach is that an investor's true preference can be 'revealed' by observing how an investor acts when faced with selection alternatives across choice scenarios. Revealed-preference tests, which are grounded in economic theory, are typically used to assess the degree to which someone is willing to lose in pursuit of a financial gain. These tests are premised on the assumption that clients act rationally and make choices that maximize their utility given certain constraints. Proponents of revealed-preference testing argue that properly designed measures reduce the effect of subjective evaluation. The primary drawback associated with revealed-preference test methodologies is that test-takers are asked to make choices based on the assumption of risk rather than uncertainty. The most common approach used to assess someone's revealed preference involves providing the decision-maker with two alternatives in which the probability of success/failure or profit/loss is known with certainty before the decision (Barsky et al. 1997; Hertwig et al. 2019).

Given that investors are rarely (if ever) presented with choice scenarios in which the outcome probabilities are known with certainty prior to decision-making, revealed-preference tests can provide misleading indications of an investor's future actions when outcomes vary from probability estimations (Frey et al. 2017). Rather than being a stable measure of a person's willingness to take risks, some argue that a revealed-preference test simply uncovers a one-time decision a test-taker makes when forced to choose between competing outcomes with known probabilities (Guiso and Sodini 2013). This explains why psychologists and scale development experts generally prefer to use elicited-risk measurement techniques as a way to gain insight into a person's willingness to engage in speculative risk (Rabbani and Nobre 2022). Sometimes called stated preference or propensity tests, elicited-risk measurement techniques are designed to uncover a test-taker's willingness to engage in a behavior or task when faced with uncertainty (Arslan et al. 2020). Scores from elicited-risk assessments are thought to provide a measure of someone's level of fiscal and emotional endurance when making financial decisions. Scores from elicited-risk tests are sometimes referred to as an investor's risk tolerance, risk aversion, or risk appetite (Rabbani and Nobre 2022). Scores are thought to provide insight into an investor's future action(s) when probabilities cannot be assigned with statistical precision prior to the point of decision.

The debate regarding whether it is more appropriate to use revealed-preference or elicited-risk measures in the context of describing and predicting household financial decision-making can be quite contentious. On one side of the debate are portfolio theorists, who argue that the only way to accurately identify an optimal portfolio is through the identification of an investor's degree of constant relative risk aversion (see Hanna and Lindamood 2004). Nearly all portfolio allocation models rely on risk aversion, as measured with some type of revealed-preference test that generates a score ranging from 1 (low risk aversion) to 10 (high risk aversion), as a model input (see Viceira 2002). In these models, risk aversion is thought to represent an investor's unwillingness to take on financial risk. On the other side of the debate are those who argue that the measurement shortcomings associated with assessing risk aversion are so problematic that derived scores provide little more than an informed guess of a person's true preference. For example, Mudzingiri and Koumba (2021) showed that revealed-preference testing methods place a high cognitive burden on test-takers. Similarly, Guiso and Sodini (2013) noted that revealed-preference tests may actually measure other personal attributes, such as numeracy and biased decision-making processes. Rather than capturing a stable preference, Frey et al. (2017) pointed out that scores derived from revealed-preference tests are transient and not indicative of a person's disposition to take on financial risk. Rather than force test-takers to choose between predefined risk alternatives, psychometricians generally argue that test-takers should be tasked with using introspective cognitions to gauge the riskiness of situations. According to Arslan et al. (2020), it is possible to estimate reliable (i.e., stable), valid, and descriptive scores using elicited-risk measures. Through the use of reference frames, it is thought that an elicited-risk test can provide an accurate insight into an investor's willingness to engage in a risky behavior in which the outcome is uncertain.

Some researchers have sidestepped the debate by arguing that risk aversion (i.e., a person's *unwillingness* to take a risk) and risk tolerance (i.e., someone's *willingness* to take action in the face of uncertainty) are opposite sides of the same coin (Mondello 2023). Barsky et al. (1997) put forward this argument. When presenting their reasoning, Barsky et al. contended that rather than viewing risk aversion differently than risk tolerance, the two constructs should be viewed as inverse concepts. Conceptually, Barsky et al.'s reasoning is that risk aversion (measured as a revealed-preference score) and risk tolerance (measured as an elicited-risk score) can be viewed as inverse substitutes. There is one substantial conceptual problem associated with the notion that risk aversion and risk tolerance are inverse substitutes. At their core, these constructs differ in what is being measured. Risk—a statistical measure of probability or outcome likelihood—is at the core of any valid revealed-preference test, whereas with an elicited-risk test, the core concept measured is uncertainty—the ambiguity of an outcome when a decision is made with incomplete information.

The purpose of this paper is to present an alternative way of viewing risk aversion and risk tolerance. Instead of regarding these constructs as competing or as inverse substitutes, we argue that risk and uncertainty and, by extension, risk aversion and risk tolerance, are complementary concepts. When conceptualized this way, the inclusion of risk-aversion and risk-tolerance scores in a model designed to describe financial risk-taking behavior should increase the amount of explained variance over a model that uses either risk aversion or risk tolerance alone. The remainder of this paper describes the theoretical orientation of the paper. This is followed by a description of the data and methodology used to examine the degree to which risk aversion and risk tolerance are complementary. The paper concludes with a presentation of the results and a discussion of the findings.

2. Theoretical Considerations

Although similar, risk aversion and risk tolerance differ in that risk aversion describes a person's preference for certainty when making a choice that involves the possibility of a loss, whereas risk tolerance describes someone's comfort associated with engaging in risky behavior (Rabbani and Nobre 2022). A risk-averse investor will prefer a guaranteed outcome over a gamble with a potentially larger payout. Likewise, an investor with a low degree of risk tolerance will exhibit a general unwillingness to engage in behaviors where the outcomes are unknown and potentially negative.

Risk aversion is measured as a choice between outcomes in which the risk and probability of return are known prior to the decision. The measurement of risk tolerance is independent of known outcome probabilities. Risk tolerance is essentially a measure of someone's comfort with uncertainty. Risk aversion, rather than risk tolerance, underlies utility theory in the construction of portfolios. A risk-averse investor will have a concave utility function, which suggests that the marginal utility of wealth or consumption decreases as wealth increases. In the context of modern portfolio theory (MPT) (Markowitz 1952), an investor's optimal portfolio is the one where the investor's utility function tangentially intersects the efficient frontier.

If risk aversion, which forms the basis of an investor's utility function, accurately describes portfolio choices, then the question of whether risk aversion or risk tolerance are substitutive or complementary constructs becomes irrelevant, and investors should focus on accurately measuring risk aversion. However, the evidence suggests that risk aversion is not a particularly good indicator of investor behavior.

Consider the equity premium puzzle. According to Mehra and Prescott (1985), the difference between average stock and risk-free returns is around five to seven percent. This equity premium cannot be explained by any currently used measures of investor risk aversion. The only way to explain an equity premium this large is to suggest a level of risk aversion that has yet to be observed across studies.

The equity premium puzzle calls into question the accuracy of using risk aversion alone in describing portfolio choices. The size of the observed equity premium suggests that investors are either extremely risk-averse or that there is some other factor at play that portfolio models are not capturing. Stated another way, standard models, with reasonable levels of risk aversion and consumption smoothing behavior, cannot generate an equity premium as large as the one observed historically. This implies that CRRA alone is insufficient to describe portfolio choices. We hypothesize that it is the combination of financial risk aversion (FRA) and financial risk tolerance (FRT) that may help account for investor anomalies like the equity premium puzzle. Specifically, FRT may complement FRA by providing insight into an investor's sensitivity to losses and comfort with taking on portfolio risk. Rather than being inverse substitutes, FRA and FRT may act together to describe investor behavior.

To test this possibility, this study extends the heuristic model of behavior proposed by Lewin (1936), which is noted as:

$$B = f(P,\ E) \tag{1}$$

where B is behavior, P represents the person, and E is the environment in which a person lives. Lewin noted that the vector of person variables includes someone's history, demographic profile, motivations, and personality, whereas the environment encompasses a vector of variables related to someone's physical and social surroundings. Someone's financial knowledge, financial risk aversion (i.e., unwillingness to take a financial risk with known outcomes), and financial risk tolerance (i.e., willingness to take a financial risk with unknown outcomes) represent person-level variables in the formula, whereas describing how an investor makes financial decisions is an example of an environmental variable. In alignment with behavioral theory showing that a person's willingness to take risk explains variance in behavioral intentions (Anderson et al. 2024), it is assumed that FRA and FRT precede engagement in risk-taking behavior. While investment results may inform future preferences, it is reasonable to assume that the path to describing portfolio risk begins by understanding an investor's preferences.

Rather than view risk aversion and risk tolerance as inverse substitutes, this study proposes that risk aversion and risk tolerance are complements of a universal set of elements. Assuming A is risk aversion, which contains a set of elements with a universal set U, then

$$\hat{A_c} = \{\mathrm{x}|\mathrm{x} \in \mathrm{U} \text{ and } \mathrm{x} \notin \mathrm{A}\} \tag{2}$$

where $\hat{A_c}$ is risk tolerance, a complement of a set A with respect to the universal set U, so that $\hat{A_c}$ contains all elements in U that are not in A.

Using this proposition, Lewin's (1936) framework can be modified as follows:

$$P_R = f\left(\left(Z_d, A, \hat{A_c}\right), E\right) \tag{3}$$

where P_R is the portfolio risk exhibited by an investor (i.e., a proxy for behavior), Z_d is a vector of demographic person-level variables, A is an investor's degree of risk aversion (FRA), $\hat{A_c}$ is the investor's risk tolerance (FRT), and E includes the environmental factors that encompass investment behavior. For the outcome (P_R), value-at-risk (VaR) was utilized as a proxy for investing behavior in this study. VaR represents the distribution of portfolio returns (Christoffersen et al. 2001), which indicates a behavioral outcome associated with taking (or avoiding) risk. There are multiple ways to estimate VaR. The approach utilized in this study is presented in the methods section below.

To summarize, in this model, FRA and FRT are hypothesized to be complementary factors. In alignment with Hertwig et al. (2019), this hypothesis is premised on the notion that measurement traditions lead to FRA serving as an indicator of transient states of preference, which tend to be influenced by memories, numeracy skills, and experiences. FRT tends to exhibit higher temporal stability and is akin to other psychological traits. As such, rather than view FRA and FRT as 'opposites side of the same coin', this study proposes that these constructs give a unique insight into a financial decision-maker's risk profile.

3. Methods

3.1. Sample

Data for this study were collected online between late 2018 and early 2022 from a sample of 30,760 individual financial decision-makers. Data included responses to an online survey hosted by College of Agriculture, Food and Natural Resources, Division of Applied Social Sciences at the University of Missouri. The survey was open to anyone with internet access and included risk-aversion, risk-tolerance, financial knowledge, and demographic questions. The questions in the survey are widely used by financial advisors in the United States when measuring their clients' risk attitudes before assigning assets. For individuals, the survey is often used to understand their own willingness to take financial risk and analyze investment preferences. Links to the survey have been and continue to be widely distributed through the U.S. Cooperative Extension Service, personal finance textbooks, and consumer sites. The survey is free to use and open to anyone with access to the internet.

3.2. Outcome Variable

The outcome variable of interest in this study was the portfolio value at risk (VaR). VaR represents the potential loss an investor might experience over a specified period of time (Jorion 2007). Estimates of VaR require portfolio mean, standard deviation, and correlation data. The following discussion describes how these statistics were estimated.

Respondents were first asked to indicate the percentage of their personal and retirement savings and investments (excluding their personal residence) that they had invested in the following asset classes at the time of the survey: (a) cash, such as savings accounts, CDs, or money market mutual funds; (b) fixed-income investment, 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, and (d) others, such as gold and collectibles. Data from 1973 through 2022 for three-month Treasury bill returns, 10-year Treasury bond returns, S&P 500 total returns, and annualized returns from gold were used as proxies for these categories to make mean and standard deviation estimates for respondent portfolios. Table 1 indicates the geometric average return and standard deviation for each asset class, as well as the correlations across the asset classes.

Table 1. Mean and standard deviation returns and correlations across the asset classes.

Asset	Mean	SD	Cash	Fixed-Income	Equities	Other
Cash	4.34%	3.20%	1.00			
Fixed-Income	6.12%	9.62%	0.1234	1.00		
Equities	10.24%	17.49%	0.1030	0.0348	1.00	
Other	6.91%	28.52%	−0.0087	−0.2230	−0.2237	1.00

Note: All correlation coefficients were statistically significant at the $p < 0.05$ level.

Using data from Table 1, the standard deviation for each portfolio was estimated using the following equation:

$$\sigma_p = \sqrt{\begin{array}{l}(W_1^2\sigma_1^2 + W_2^2\sigma_2^2 + W_3^2\sigma_3^2 + W_4^2\sigma_4^2 + 2W_1W_2Cov_{1,2} + 2W_2W_3Cov_{2,3} + \\ 2W_1W_3Cov_{1,3} + 2W_1W_4Cov_{1,4} + 2W_2W_4Cov_{2,4} + 2W_3W_4Cov_{3,4})\end{array}} \quad (4)$$

where, $W_1^2\sigma_1^2$ = weighted variance of cash, $W_2^2\sigma_2^2$ = weighted variance of fixed-income assets, $W_3^2\sigma_3^2$ = weighted variance of equities, and $W_4^2\sigma_4^2$ = weighted variance of other assets, W is the weight of the asset in the portfolio, σ is the standard deviation of the asset, and Cov is the covariance between two of the assets in the portfolio.

VaR was then calculated for each respondent based on their reported allocation of assets to the four investment classifications (i.e., cash, fixed-income, equities, and other) using the following formula:

$$\text{VaR} = Mean\ Return - (1.96 \times Portfolio\ SD) \quad (5)$$

where VaR represents the predicted worst-case loss with a 95% confidence level (z = 1.96).

3.3. Financial Risk Aversion

Financial risk aversion (FRA) was measured using a new revealed-preference type item. An answer to the question was thought to approximate a respondent's level of constant relative risk aversion (see Grable et al. 2020 for a description of the methodology used to test the validity of the item):

> Suppose you are considering making an investment. You have a chance to make an investment that will return either \$50,000 or \$100,000. Your financial advisor estimates that the probability of receiving \$50,000 is 50% and the probability of receiving \$100,000 is also 50%. You also learn from your financial advisor that shares in this investment are limited and difficult to obtain. Therefore, the less you are willing to invest, the lower the chance that you will be able to participate in the investment. Based on this information, what is the largest amount of money you would be willing to pay to participate in this investment, assuming you had the money?

The following choice options were provided: (1) \$70,700, (2) \$66,667, (3) \$63,246, (4) \$60,571, (5) \$58,566, (6) \$57,083, (7) \$55,978, (8) \$55,143, (9) 54,499, and (10) \$53,991. These dollar figures represent the mathematical certainty equivalent amounts associated with the measure (i.e., the dollar amounts correspond to differing levels of constant relative risk aversion). Risk aversion increases as the dollar amount of investment decreases. To make the use of the responses more realistic, risk seekers (i.e., those with a risk-aversion score of 1.0) and risk avoiders (i.e., those with a risk-aversion score of 10.0) were excluded from the analyses. This delimitation procedure was implemented to remove outliers whose scores were at the extreme (e.g., someone with a risk-aversion score of 1.0 has an almost unlimited disposition to take financial risk, whereas someone with a score of 10.0 has an almost certain unwillingness to invest in any asset that exhibits price volatility). The resulting distribution of FRA scores is shown in Figure 1.

As a validity check, FRA scores were correlated with cash, fixed-income, and equity holdings. The correlation coefficients were 0.078, 0.026, and −0.101, respectively, for cash, fixed-income, and equities. Although the effect sizes were small for cash and fixed-income holdings, the associations were statistically significant, suggesting that the FRA scores were related to risk-taking in a manner consistent with portfolio theory.

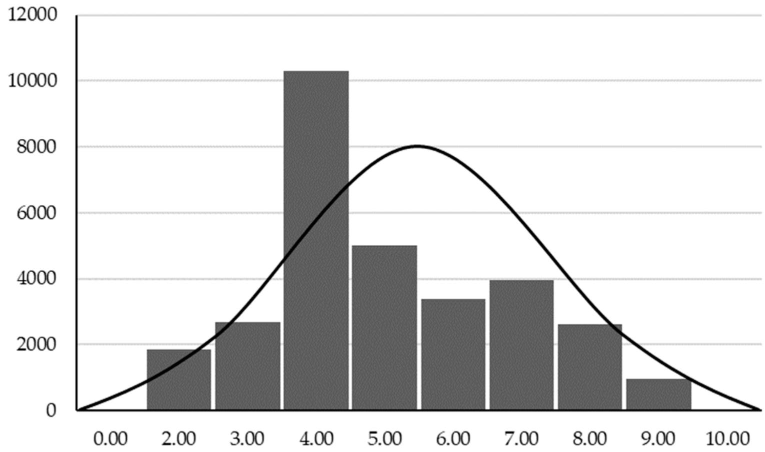

Figure 1. Distribution of FRA scores across the sample.

3.4. Financial Risk Tolerance

Financial risk tolerance (FRT) was assessed using an elicited-preference scale. Specifically, a 13-item risk-tolerance questionnaire, originally published by Grable and Lytton (1999), was used to estimate the respondent's willingness to take a financial risk. Scores across the scale's 13 items were summed, with higher scores indicating a greater willingness to take financial risk. Scores in this study ranged from 13 to 47. Cronbach's alpha was 0.71, which was similar to the reliability estimates reported in the literature (e.g., Amonhaemanon 2022; Beer and Wellman 2021; Chung and Au 2020; Kuzniak et al. 2015; Lucarelli et al. 2011; Rabbani et al. 2017; Thanki and Baser 2021; Uckun and Dal 2021).

3.5. Other Personal and Environmental Variables

In alignment with previous reports (e.g., Cruciani et al. 2022; Thompson et al. 2022; Vandone and Ottaviani 2011), the following control variables were included in this study. Gender (see Bajtelsmit and Bernasek 1996; Fisher and Yao 2017; Lawrenson and Dickason-Koekemoer 2020; Sung and Hanna 1996), as described by a respondent, was assessed as either male (coded 1) or female (coded 2). The following marital status categories (see Roszkowski et al. 1993; Thanki et al. 2022; Zeeshan et al. 2021) were used in the analyses: (a) married, (b) single, or (c) other, including divorced, separated, or widow(er). The married group was used as the reference category. Age (see Bajtelsmit and Bernasek 1996; Fang et al. 2021; Grable 2000; Rabbani et al. 2020) was measured using the following categories: (a) under the age of 35, (b) 35 to 44, (c) 45 to 54, (d) 55 to 64, (e) 65 to 74, and (f) 75 and over. Education (see Bayar et al. 2020; Rabbani et al. 2022) was measured ordinally using the following six categories: (a) some high school or less, (b) high school graduate, (c) some college/trade/vocational training, (d) Associate's degree, (e) Bachelor's degree, and (f) graduate or professional degree. Household income (see Grable et al. 2020; Kochaniak and Ulman 2020; Oztop and Kuyu 2020; Zhong and Xiao 1995) was measured using the following five classifications: (a) less than $25,000, (b) $25,000 to $49,999, (c) $50,000 to $74,999, (d) $75,000 to $99,999, and (e) $100,000 or greater. A respondent's subjective evaluation of their financial knowledge (SFK) (see Grable and Rabbani 2023; Heo et al. 2021; Mubaraq et al. 2021) was assessed by asking each respondent to indicate, on a scale from one to five, how they would rate their overall understanding of personal finance and money management concepts and practices. Answers were coded as 1 for very low and 5 for very high. Lastly, respondents were asked how they make financial and investment decisions (see Baeckström et al. 2021; Cruciani et al. 2022). Those who reported that either they or someone in their household was responsible for these decisions were coded as 1, whereas those who stated that they relied on the advice of a financial advisor were coded as 0.

3.6. Data Analyses

Descriptive statistics were calculated to describe the demographic and behavioral characteristics of the sample. Correlations between categories of FRA and FRT were also estimated. The primary analyses consisted of the estimation of a series of regression models. The regressions were utilized to determine the degree to which FRA and FRT are complementary in describing portfolio VaR. As shown in Equation (10), a centered interaction term between FRA and FRT was incorporated into the model. The interaction was included to determine the degree to which one of these variables modified the other. The primary regression models were estimated as follows:

$$Model\ 1:\ Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \varepsilon \quad (6)$$

$$Model\ 2:\ Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \ \beta_9 x_9 + \varepsilon \quad (7)$$

$$Model\ 3:\ Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_{10} x_{10} + \varepsilon \quad (8)$$

$$Model\ 4:\ Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \ \beta_{10} x_{10} + \varepsilon \quad (9)$$

$$Model\ 5:\ Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_{11} + \varepsilon \quad (10)$$

where Y = portfolio VaR, X_1 = gender, X_2 = single marital status, X_3 = other marital status, X_4 = age, X_5 = education, X_6 = household income, X_7 = investment decision-making responsibility, X_8 = SFK, X_9 = FRA, X_{10} = FRT, X_{11} = centered FRA × FRT, and ε = error term.

3.7. Robustness Checks

Six robustness checks were made to confirm the regression model results. Given the sample characteristics, Equation (10) was reassessed by delimitating respondents to those older than age 35 and those aged 35 years or older with risky asset-only portfolios. This was followed by a test using only male respondents. A separate check was made using responses from those holding a Bachelor's degree level of education or higher. A similar model was tested using data from respondents with incomes of $75,000 or more. In the final model, only data from males with a Bachelor's degree level of education or higher with incomes of $75,000 or more were used.

4. Results

Table 2 shows the descriptive statistics for the variables used in this study. As shown in the table, the sample comprised relatively young, single, male respondents who indicated having a high level of financial knowledge. The majority of those in the sample also reported that they are responsible for making their own investment decisions. While the sample is not generalizable to the U.S. population, it is worth noting that, because of the sample size, each demographic category included a relatively large number of respondents.

Table 3 shows the correlations across the FRA, FRT, and VaR variables. As expected, the relationship between FRA and FRT was negative, implying that as risk aversion increased, risk tolerance decreased. Although the relationship was statistically significant, the effect size was modest, suggesting that FRA and FRT should not necessarily be viewed as 'opposite sides of the same coin'. The correlation coefficients related to VaR provide evidence that the FRA and FRT measurement tools were related to VaR in the predicted manner. Specifically, the portfolios of respondents exhibited less risk as risk aversion increased. Similarly, as risk tolerance increased, the variance in respondent portfolios increased.

Table 4 shows the results from the five core regression models. The effect of the independent variables was assessed using beta weights (β). Model 1 shows the relationships between VaR and the personal and environmental control variables used in this study. All but two variables (i.e., other marital status and income) were significantly related to VaR. The portfolios of females, singles, and those who made their own financial/investment decisions exhibited less risk. The portfolios of older respondents and those with more education and financial knowledge showed greater variability in returns. Subjective financial knowledge and education were of primary importance in describing VaR.

Table 2. Descriptive profile of respondent (N = 30,760).

	Frequency	Mean	SD
Gender			
Male	62.6%		
Female	37.4%		
Age			
Under 35	72.1%		
35 to 44	13.4%		
45 to 54	7.3%		
55 to 64	4.3%		
65 to 74	1.7%		
75 and older	1.2%		
Marital status			
Married	28.0%		
Single	66.8%		
Other	5.2%		
Education			
Some high school	18.8%		
High school	13.3%		
Some college	15.5%		
Associate's degree	7.6%		
Bachelor's degree	25.8%		
Graduate/Professional	18.9%		
Household income			
Less than $25,000	21.9%		
$25,000 to $49,999	16.0%		
$50,000 to $74,999	16.7%		
$75,000 to $99,999	12.8%		
$100,000 or more	32.7%		
Financial decision-making authority			
Respondent	81.6%		
Respondent relies on advisor	18.4%		
Subjective financial knowledge			
Very low	2.9%		
Low	14.5%		
Average	43.4%		
High	30.8%		
Very high	8.4%		
FRA		5.14	1.76
FRT (α = 0.70)		28.06	4.72
VaR		−9.76	7.65

Table 3. Correlation Estimates.

	FRA	FRT	VaR
FRA	1.000		
FRT	−0.204 **	1.000	
VaR	0.098 **	−0.347 **	1.000

Note: ** $p < 0.001$.

Table 4. Regression results showing complementary relationship between FRA and FRT in describing VaR (N = 30,760).

	Model 1				Model 2				Model 3			
	b	S.E.	β	t	b	S.E.	β	t	b	S.E.	β	t
(Constant)	−0.072 **	0.002		−31.185	−0.077 **	0.003		−24.718	0.026 **	0.003		8.814
Gender	0.022 **	0.001	0.140	31.914	0.018 **	0.001	0.124	22.194	0.016 **	0.001	0.100	23.144
Single	0.008 **	0.001	0.048	7.957	0.007 **	0.001	0.040	5.104	0.008	0.001	0.048	8.110
Other marital	0.000	0.002	−0.001	−0.312	0.000	0.002	0.000	0.084	0.002 **	0.002	0.005	1.032
Age	−0.006 **	0.000	−0.097	−15.411	−0.007 **	0.000	−0.113	−13.991	−0.006 **	0.000	−0.109	−17.830
Education	−0.005 **	0.000	−0.123	−23.750	−0.004 **	0.000	−0.108	−16.148	−0.004 **	0.000	−0.090	−17.667
Income	0.000	0.000	0.008	1.678	0.001 *	0.000	0.019	3.298	0.001 *	0.000	0.011	2.549
Dec-making	0.007 **	0.001	0.035	8.203	0.006 **	0.001	0.034	6.291	0.006 **	0.001	0.031	7.418
SFK	−0.011 **	0.000	−0.136	−30.257	−0.010 **	0.000	−0.126	−22.174	−0.007 **	0.000	−0.088	−19.654
FRA					0.002 **	0.000	0.048	8.695				
FRT									−0.004 **	0.000	−0.230	−51.815
	F = 743.213, $p < 0.001$; $R^2 = 0.110$				F = 693.757, $p < 0.001$; $R^2 = 0.114$				F = 995.646, $p < 0.001$; $R^2 = 0.156$			
	Model 4				**Model 5**							
	b	S.E.	β	t	b	S.E.	β	t				
(Constant)	0.022 **	0.003		6.934	0.381	0.261		1.463				
Gender	0.016 **	0.001	0.099	22.751	1.283 **	0.054	0.085	23.576				
Single	0.008 **	0.001	0.047	8.073	0.798 **	0.086	0.051	9.228				
Other marital	0.002	0.002	0.005	1.039	0.627 **	0.097	0.027	6.473				
Age	−0.006 **	0.000	−0.110	−18.032	−0.750 **	0.031	−0.122	−24.270				
Education	−0.004 **	0.000	−0.089	−17.522	−0.247 **	0.018	−0.061	−13.928				
Income	0.001 *	0.000	0.012	2.663	0.007 **	0.017	0.001	0.391				
Dec-making	0.006 **	0.001	0.031	7.435	1.051 **	0.031	0.126	33.982				
SFK	−0.007 **	0.000	−0.088	−19.596	−0.601 **	0.030	−0.075	−20.109				
FRA	0.000 **	0.000	0.019	4.400	.047 **	0.009	0.019	5.225				
FRT	−0.004 **	0.000	−0.225	−49.258	−0.317 **	0.006	−0.204	−53.653				
FRAxFRT					0.009 **	0.002	0.018	5.250				
	F = 898.358, $p < 0.001$; $R^2 = 0.157$				F = 1346.486, $p < 0.001$; $R^2 = 0.177$							

Notes: * $p < 0.01$ ** $p < 0.001$; in Model 4, the tolerance estimates for the variables ranged from 0.490 to 0.951, whereas the VIF estimates ranged from 1.006 to 2.189. It was determined that multicollinearity was not of concern in the model.

Model 2 shows the results when FRA was added to the model. In this model, income was added to the list of statistically significant variables, with higher incomes being associated with lower levels of portfolio risk. FRA was significant. In alignment with the correlation results (Table 3), portfolio risk decreased as risk aversion increased. However, the overall effect of FRA was low. Model 3 shows the same estimation, with FRA replaced by FRT. The demographic relationships remained unchanged from Model 2. In this model, portfolio risk increased in alignment with FRT. FRT emerged as the most important descriptor of VaR across the variables of interest.

In Model 4, FRA and FRT were included in the estimation. The model was used as the first test of the hypothesis that FRA and FRT are complementary constructs. The demographic relationships remained unchanged from Models 2 and 3. The relationship between FRA and VaR was positive, suggesting that a respondent's portfolio risk declined as risk aversion increased. The opposite relationship was noted between FRT and VaR. As a respondent's risk tolerance increased, so did the risk exhibited in their portfolio. Evidence of the complementary nature of FRA and FRT can be seen in the beta coefficients. FRT was the most important descriptor of portfolio risk in the model. While FRA was statistically significant, FRA was more important in terms of adding a nuanced contribution to the amount of explained variance in VaR. It appears that financial decision-makers use both their transient preference for risk and their more stable trait-like risk tolerance to frame an investment opportunity before making an investment decision. In this way, FRA and FRT can be viewed as complementary constructs.

Model 5 shows the results with a centered interaction term between FRA and FRT. This test was made to confirm the hypothesis that FRA and FRT can be complementary constructs. Adding the interaction term to the model provided additional clarifying support for the nature of the association between VaR, FRA, and FRT. The results indicate that there is a negative association between FRA and VaR, subject to the level of FRT. In this study, FRT scores ranged between 13 and 47. FRA showed a positive association with VaR when FRT was above 23.22, and a negative association when FRT was below 23.22. In this sample, the average FRT score was 28.06 (+/−4.72), which indicates that for a sample of the population with an average FRT score, FRA is positively associated with VaR. On the other hand, the association between FRT and VaR is negative, subject to the level of FRA. In this study, FRA ranged between 2 and 9, and within this range, the association between FRT and VaR remained negative. To summarize, FRA and FRT had significant main effects across the models. In Model 5, the statistically significant interaction effect indicates that FRT makes an additional contribution to FRA, which adds support to the notion that FRA and FRT act as complements rather than substitutes.

Table 5 shows the robustness check results. Although the statistical significance of some of the personal and environmental control variables changed based on the sample delimitations, the effect of FRT was consistent across the six models. As a respondent's risk tolerance increased, so did the risk exhibited in their portfolio. FRT exhibited the largest model effect across the models. The effect of FRA showed greater variation. Statistical significance between FRA and VaR was noted in the (a) older than age 35 model, (b) the male only model, and (c) the Bachelor's degree or higher model; however, FRA was not significant in the other tests. The centered interaction term between FRA and FRT was only significant in the male only model.

Table 5. Robustness checks using gender, age, education, and income.

	Older than 35 (N = 14,657)				**Older than 35 with Diversified Portfolio (N = 1168)**				**Males Only (N = 40,355)**			
	b	S.E.	β	t	b	S.E.	β	t	b	S.E.	β	t
(Constant)	2.039 **	0.607		3.360	−19.794 **	2.313		−8.556	1.773 **	0.334		5.309
Gender	0.898 **	0.125	0.058	7.199	0.453	0.527	.027	0.859				
Single	0.387 *	0.180	0.017	2.149	0.140	0.749	.006	0.187	0.927 **	0.119	0.057	7.808
Other marital	0.529 **	0.154	0.028	3.435	−0.548	0.588	−0.028	−0.932	0.767 **	0.137	0.030	5.606
Age	−0.424 **	0.060	−0.056	−7.099	0.148	0.242	0.018	0.612	−0.588 **	0.042	−0.093	−13.866
Education	−0.290 **	0.049	−0.047	−5.901	0.393 *	0.188	0.062	02.087	−0.324 **	0.024	−.077	−13.389
Income	−0.242 **	0.044	−0.045	−5.466	0.653 **	0.169	0.121	03.862	0.067 *	0.023	0.014	2.859
Dec-making	1.452 **	0.091	0.128	15.963	−.069	0.399	−.005	−.173	1.262 **	0.044	0.140	28.684
SFK	−0.703 **	0.064	−0.093	−11.060	0.005	0.250	0.001	0.018	−0.695 **	0.042	−0.082	−16.632
FRA	0.051 *	0.017	0.023	2.915	0.016	0.071	0.007	0.225	0.052 **	0.012	0.020	4.299
FRT	−0.368 **	0.013	−0.231	−27.616	−0.189 **	0.052	−0.117	−3.648	−0.334 **	0.008	−0.205	−41.501
FRAxFRT	0.006	0.003	0.014	1.873	0.024	0.013	0.056	1.806	0.007 **	0.002	0.014	3.011
	F = 225.158, $p < 0.001$; $R^2 = 0.144$				F = 4.753, $p < 0.001$; $R^2 = 0.034$				F = 780.514, $p < 0.001$; $R^2 = 0.162$			
	Bachelor's Degree or Higher (N = 25,724)				**Income ≥ $75,000 (N = 27,844)**				**Males, Bachelor's Degree or High, & Income ≥ $75,000 (N = 7375)**			
	b	S.E.	β	t	b	S.E.	β	t	b	S.E.	β	t
(Constant)	1.093	0.626		1.746	6.517 **	0.546		11.942	7.896 **	1.307		6.041
Gender	1.265 **	0.093	0.081	13.623	0.943 **	0.083	0.063	11.395				
Single	0.718 **	0.116	0.046	6.206	0.327 **	0.128	0.022	2.546	0.343	0.214	0.021	1.605
Other marital	0.633 **	0.127	0.031	4.974	0.094	0.140	0.004	0.671	0.328	0.223	0.017	1.471
Age	−0.656 **	0.041	−0.113	−16.179	−0.792 **	0.042	−0.151	−18.633	−0.465 **	0.063	−0.093	−7.362
Education	−0.113	0.092	−0.007	−1.232	−0.403 **	0.028	−0.106	−14.278	−0.094	0.155	−0.007	−.604
Income	−0.111 **	0.031	−0.023	−3.568	−0.831 **	0.084	−0.052	−9.849	−1.080 **	0.176	−0.067	−6.138
Dec-making	1.575 **	0.061	0.155	25.847	1.099 **	0.051	0.122	21.719	1.782 **	0.140	0.139	12.728
SFK	−0.748 **	0.049	−0.096	−15.376	−0.941 **	0.045	−0.121	−20.922	−1.279 **	0.089	−0.165	−14.410
FRA	0.050 **	0.014	0.021	3.618	0.025	0.013	0.010	1.866	0.027	0.025	0.013	1.077
FRT	−0.375 **	0.010	−0.225	−36.574	−0.309 **	0.009	−0.201	−34.405	−0.365 **	0.018	−0.231	−19.939
FRAxFRT	0.004	0.003	0.008	1.386	0.007 *	0.003	0.014	2.705	0.006	0.005	0.015	1.270
	F = 526.270, $p < 0.001$; $R^2 = 0.183$				F = 792.587, $p < 0.001$; $R^2 = 0.238$				F = 155.590, $p < 0.001$; $R^2 = 0.173$			

Notes: * $p < 0.01$ ** $p < 0.001$.

5. Conclusions and Discussion

Household financial decision-makers' risk aversion and risk tolerance are generally assumed to be 'opposite sides of the same coin'. When viewed this way, FRA and FRT can be seen as inverse substitute constructs. The purpose of this study was to determine whether FRA and FRT are, in fact, substitutes or whether these individual characteristics are complementary. In this regard, it was determined that FRA and FRT are inversely related, as one might expect. However, the effect size of the correlation was relatively small. In order for FRA and FRT to be true substitutes, the level of association between these two constructs should have been much higher than what was observed.

Multivariate tests showed a similar pattern of association between FRA and FRT. In each of the models (see Tables 4 and 5), FRA and FRT were observed to have opposite effects with portfolio variance. FRT exhibited the largest effect on VaR. While FRA was significant across the core models (but not across the robustness checks), its effect was smaller. The amount of explained variance in VaR was highest when FRA and FRT were modeled jointly. The statistically significant interaction effect in Model 5 indicates that FRA and FRT add to each other in terms of describing portfolio volatility. This implies that, as hypothesized in this study, FRA and FRT can be viewed as complementary constructs.

The findings from this study have implications for research and investment management. To begin with, if measures of FRA and FRT are available in a single dataset, researchers should consider including both in models designed to describe or predict household financial decisions and investment behavior. Of course, the correlation between measures should first be estimated to ensure that multicollinearity is not an issue, but if the results from this study are indicative of what a researcher can expect, the correlation should not be particularly large. The primary reason for expecting a low association effect size is that FRA and FRT are measuring two different personal characteristics. In the former, FRA is likely measuring a transient preference. In the latter, FRT is measuring a trait-like characteristic that should exhibit greater stability over time. Combining these two measures can provide a researcher with a deeper insight into household financial managers' perspectives and ultimately, their behavior.

More research is needed to document the transient versus trait-like characteristics of FRA and FRT. This means that FRA test developers need to provide more precise estimates of reliability and validity when arguments are made that FRA can be used as an inverse proxy for FRT. Until these data are more widely publicized, investment managers and others who provide advice to households regarding investment and asset allocation choices should be aware of the limitations and advantages associated with using measures of FRA or FRT separately. As the results from this study suggest, if possible, those who provide investment advice to others and those who are tasked with mapping risk attitudes to portfolio compositions should consider accounting for both FRA and FRT when formulating recommendations.

The results also provide some insight into the equity premium puzzle (Mehra and Prescott 1985). While risk aversion alone does not capture the behavior of investors in ways that explain anomalies like the equity premium puzzle, the inclusion of FRT in portfolio models may help to describe consumption and saving behaviors that occur in markets characterized by uncertainty. Although more research is needed, we believe that it is the combination of a person's comfort with engaging in behaviors in which the outcome is both uncertain and potentially negative, and a preference for certainty, measured as FRT and FRT, respectively, that offer the greatest level of explained variance in investment models.

While the findings from this study are noteworthy, it is worth considering a few possible limitations associated with the analyses presented in this paper. To begin with, data were collected over a multi-year period from an open-access online platform. It was not possible for the research team to pre-screen or design the sample to be nationally representative. To account for this limitation, we subjected the initial analyses to additional robustness checks, but it is still possible that the use of a nationally representative sample might indicate that FRA and FRT are not complementary but rather, are substitute constructs. Readers should also recognize that the measure of FRA used in this study was designed to be a quick and easy-to-administer indicator of FRA. It is possible that if a longer, more traditional, revealed-preference test had been used, the correlational data presented in this paper may have changed. Issues related to endogeneity should also be considered. In this study, it was assumed that FRA and FRT explain behavioral intentions and precede engagement in risk-taking behavior. It is possible that investment variance explains FRA and FRT. Future studies are needed to examine this possibility. Finally, the timing of the data collection may have skewed responses in a way that differs from long-term norms. Data were collected during the COVID-19 pandemic and a controversial U.S. Presidential election. Follow-up studies are needed to confirm the findings presented in this paper. Nonetheless, results from the large and delimited samples used in this study suggest that rather than viewing FRA and FRT as 'opposite sides of the same coin', FRA and FRT are likely to be complementary constructs.

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