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Development and Validation of a Model and Measure of Financial Risk-Taking

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This study presents a theoretical model and assessment tool that measures individual differences in risk-aversion in financial matters. Unlike other measures of financial risk-taking, this measure assumes no prior technical knowledge of finance. The assessment tool was developed using item response theory as well as classical test theory methods. The measure is tested for predictive validity through various procedures and proves to have those properties. In addition the measure is tested for construct validity using structural equation modeling and allows for the successful classification of individuals in one of four classifications: Non-Investor, Risk Managing Investor, Conservative Investor, and Speculator. We discuss potential applications of this measure.

Introduction

Recent events such as the decrease of the Standard and Poor's 500 Index by over 60% and the simultaneous drop of the Dow Jones index have made individual investors more aware of the risks involved with investing money in the equity markets. This recent drop was a shock to many investors who believed that their investments were relatively risk-free. Given these recent developments, we saw an opportunity to develop a tool to evaluate the level of risk an individual is willing to take with his or her personal investment independent of the individual's knowledge in the area of financial investments. So far the Deutsche Bank, for example, evaluates their customers' risk preference through an interview with one of their investment bankers by asking questions regarding experience and preference and categorizes the customer on a continuum ranging from 1 (very risk averse) to 5 (risk seeking). This initial evaluation is designed to prevent the customer from buying securities through on-line banking that exceed his or her risk level. Other institutions evaluate financial risk-taking with questions that capture investment horizon, cash flow preferences, and self-classifications of the customers (e.g. low-risk preference, moderate-risk preference, high-risk preference). These measures have typically not been evaluated using psychometrics normally used to assess individual difference measures of psychological constructs. In addition, these measures are typically not based on a theoretical understanding of the concept of risk. Given these limitations, there is a need to develop and evaluate a measure based on consideration of relevant research and theory.

General Findings Regarding Risk

Early research had indicated that risk-taking is not a uniform trait that can be generalized over various activities (Flanders [1970], Goodman [1970], Higbee [1971], Slovic [1972], E. Weinstein and Martin [1969], M. S. Weinstein [1969]). For example, a person can display great risk-taking (or sensation seeking) in a hobby but be a conservative investor. Research has shown that general measures of risk seeking or sensation seeking do not predict financial risk-taking well. For example, Morse (Morse [1998]) found no significant correlation between sensation seeking and the preferred risk level in investments by the participants. After a review of the literature, Slovic [1972, p.795] concluded that,

> only those tasks highly similar in structure and involving the same sorts of payoffs (e.g. all financial, all social, etc.) have shown any generality and, as similarity decreases, these cross-tasks consistencies rapidly decline.

Given this it seems necessary to determine an individual's risk-taking behavior domain specific. Various areas of risk-taking that have been explored are sexual risk-taking behavior (Luster & Small [1994], Yeh [2002]), leisure activities (McIntyre [1992], Schrader and Wann [1999], Schuett [1993]), drug use (Cherpitel [1999]), and financial risk-aversion (J. Grable and Lyt-

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ton [1999], J. E. Grable [2000], Masters [1989], Morse [1998], Shapira [1995]).

Review of Existing Research Regarding Financial Decision Making and Risk

The majority of the research conducted in the area of measuring individual risk-taking behavior analyzes the factors that influence financial risk-taking behavior. The focus has been on various demographic characteristics such as gender, age, martial status, profession, income, education, and finance specific knowledge. Results so far display that males seem to be more risk tolerant then females (J. E. Grable [2000], Hawley and Fujii [1993], Powell and Ansic [1997], Wong and Carducci [1991]), older respondents seem to be more risk tolerant than younger respondents (J. E. Grable [2000], Hawley and Fujii [1993]), married respondents seem to be more risk tolerant than single respondents (H. K. Baker and J. A. Haslem [1974], J. E. Grable [2000], Masters [1989]), professionals seem to be more risk tolerant than non-professionals (H. K. Baker and J. A. Haslem [1974], J. E. Grable [2000], Masters [1989]), respondents with higher income seem to be more risk tolerant than those with lower incomes (J. E. Grable [2000], Hawley and Fujii [1993]), respondents with more education seem to be more risk tolerant than others (J. E. Grable [2000], Hawley and Fujii [1993]), respondents with higher levels of financial knowledge seem to be more risk tolerant than others (J. E. Grable [2000], Masters [1989]), and respondents with greater economic expectations seem to be more risk tolerant than those with less expectations (J. E. Grable [2000]). The above-mentioned research was primarily concerned with influencing factors on risk-taking behavior, where risk-taking was measured by choices that individuals made when faced with certain investment options, risky decisions, or gambles.

There have been several efforts to develop a psychometrically reliable individual difference measure of financial risk-taking. The most recent attempt to measure individual risk-taking and development of a scale was undertaken by Grable [1999]. In his research Grable developed a risk assessment instrument consisting of 13 items covering eight dimensions, 'guaranteed vs. probable gamble', 'general risk choices', 'choice between a sure loss and a sure gain', 'risk as experience and knowledge', 'risk as level of comfort', 'speculative risk', 'prospect theory', and 'investment risk'. The scale demonstrated acceptable reliability; however, the only validation evidence presented was a positive correlation with a one-item measure that assessed tolerance for risk (Item: Which of the following statements on this page comes closest to the amount of financial risk that you are willing to take when you save or make investments? a) Take substantial financial risk expecting to earn substantial returns, b) Take above average financial risks expecting to earn above average returns, c) Take average financial risks expecting to earn average returns, and d) Not willing to take any financial risks). Grable acknowledges the problems that are associated with such a measure as the only validation method; unfortunately, to our knowledge, further validation research has not been conducted on this index.

In addition to methodological criticism, this scale can be critiqued on conceptual and practical grounds. For instance the dimension 'general risk choices' seems to be too broad to measure the specific risk-taking in financial investments. A similar argument can be applied to the dimension 'risk as experience and knowledge' where the experience of the individual is evaluated. This dimension does not really measure risk-taking preferences but is a test of finance knowledge. It will be influenced by what financial theory proclaims to be the correct viewpoint on risk and risk-taking but not the individual's risk-taking propensities. In addition the dimension 'choice between a sure loss and a sure gain' becomes irrelevant when considering the area of financial investments because of the fact that the investor will not deliberately choose an investment that promises a negative return; his or her goal is to maximize the return. Further on the evaluation of the dimension 'investment risk' by the individual assumes some knowledge regarding financial investments. Because our scale is supposed to measure risk-aversion and not knowledge it seems appropriate to not include these dimensions in the questionnaire.

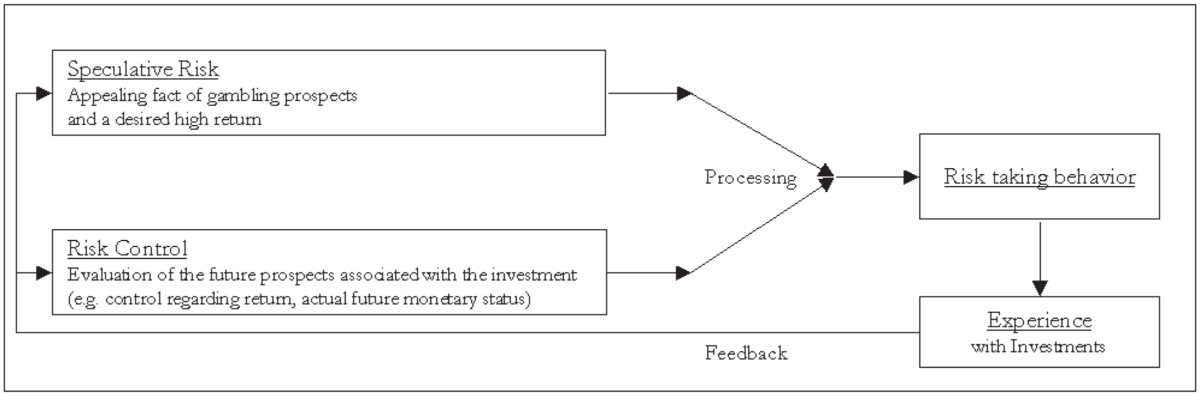
Another detail that has not been mentioned in this context is the fact that items that use specific dollar amounts (62% of all items) might lead to the artifact of measuring the individual's monetary value system instead of isolating the risk-taking behavior. Various research has shown that perception of monetary value differs among individuals from various economic backgrounds (Bruner and Goodman [1947]). To avoid this artifact, the items should remain unspecific regarding dollar amounts to allow for a proper isolation of risk-taking.

Given all of these concerns, it seems that some of Grable's items might contaminate results and measure other concepts than financial risk-taking. In conclusion, different dimensions have to be developed following a different approach and model.

Theoretical Framework for Current Measure

The claim of this paper is that risk-aversion in financial investments is determined by two factors, *speculative risk* and *risk control*. The two dimensions are based on the risk-taking and risk-aversion concepts introduced in the economics and finance literature. Tra-

FIGURE 1
Risk-Taking Model



ditionally the terms risk-taking and risk-aversion describe a continuum with the end points characterizing a 'risk-averse' or 'risk-taking' individual. Our model allows for a classification of the individual on this dimension through the usage of two additional constructs, speculative risk and risk control. Speculative risk can be described as a force that indicates the individual's tendency toward the risk taking side, whereas risk control as a counterforce indicates the individual's tendency toward the risk averse side. By evaluating both forces, this research provides a framework that allows for the successful classification of the individual on the risk taking—aversion continuum.

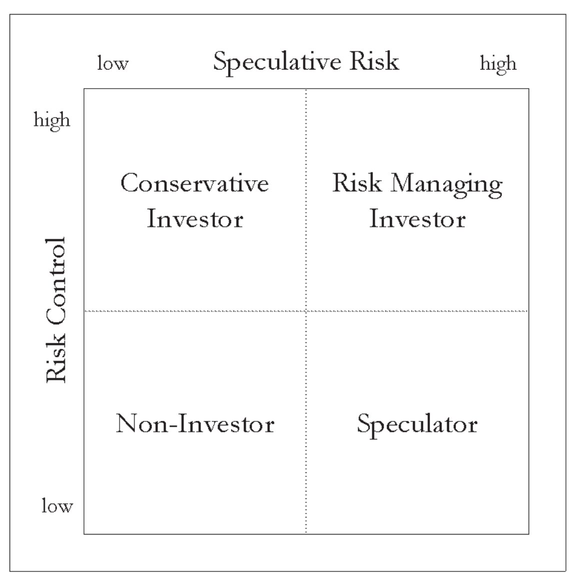
Speculative risk captures the gambling behavior of the individual and the tempting option that by accepting a higher level of risk the expected return will increase. This concept was also used by Grable who developed a scale that measured risk-aversion using gambles to determine whether the individual likes to speculate or has a more conservative preference (J. E. Grable [2000]). Risk control influences the decision maker by reminding him/her that by accepting a higher level of risk the potential of future losses will increase. In this paper risk control is assessed evaluating measures such as the control over the expected return, the certainty of the future expected cash flows, and the expected future monetary status. In an evaluative step the individual evaluates her or his level of speculative risk and modifies it by her or his risk control level resulting in the ideal level of risk-taking while also considering the consequences.

The model is, contrary to financial theory, interactive in that speculative risk as well as risk control will be influenced by the previous investment experience and knowledge. Individuals with previously high risk control and moderate speculative risk will, as they are positively reinforced, increase their speculative risk and decrease their risk control. These individuals will be reinforced as long as their results yield high returns and engage more and more in high-risk strategies, whereas negative results (losses) will lead to a reevaluation of the two dimensions causing them to employ a more conservative approach, as could be observed in the financial markets during the last years. For a graphical display of the model see Figure 1.

Contrary to current financial theory, where it is generally assumed that investors are strictly risk-averse (Brigham [2002], p. 244; Emery [1998], p. 181), this model assumes that for some individuals the thrill of speculating (speculative risk) is larger than the individuals risk-aversion (risk control). These individuals are labeled 'Risk Seekers' whereas individuals with a focus on risk control compared to the speculative risk are labeled 'Risk Averters'.

The model also allows for a classification of the subjects into four quadrants, see Figure 2. The classification is determined by the individuals score on both

FIGURE 2
Risk-Taking Matrix



scales, which allows them to be categorized as '*Conservative Investor*', '*Risk managing Investor*', '*Speculator*', or '*Non-Investor*'. The following part of the paper will evaluate the model by empirically verifying some of the relationships through the development of scales that measure speculative risk and risk control.

Goals of the Study

The goals of the current study are to test the above-mentioned model as well as to develop an instrument consistent with the model. The assessment tool is intended to be used in screening procedures of investment houses, banks, or for personal financial planers to allow for a quick knowledge independent assessment of the clienteles risk preference leading to a personalized investment plan. The resulting scale should be easily administered and scored. The scale will be evaluated using advanced statistical procedures ensuring reliability as well as unidimensionality of the resulting scales. The model will also be validated through the confirmation of previous research findings as well as through its predictive ability. Finally, a different dataset will be used to confirm the theoretical model using discriminant analysis and structural equation modeling.

Method

Operationalization of the Model

The model includes two theorized dimensions that have an impact on the risk-taking behavior. The process termed 'Processing' of speculative risk and risk control in the model (see Figure 1) and derivation of an overall measure for *Risk taking behavior* is operationalized by subtracting speculative risk from risk control. We argue that the dimension of risk control decreases the amount of risk-taking, whereas the dimension of speculative risk encourages it. The difference between the two scales will determine the risk-taking behavior and is called *risk-aversion score*. It is hypothesized that the higher the individual scores on the obtained risk-aversion score the more risk-aversion regarding financial investments the subject will display.

One of the difficulties in developing such an instrument lies within the fact that investment decisions deal with monetary values. Some individuals might consider the loss of $1,000 to be a large loss whereas others might evaluate it as a minor loss. This perception of loss depends on various factors, such as the socioeconomic background, income, and consumption preference. It is important that the scale measures risk-taking propensities *independent of the individual's monetary value system*. The items therefore should not include any dollar amounts that would elicit an evaluation by the individual's value system. At the same time the problem of anchoring effects is avoided if items without dollar amounts are used. It is necessary to ensure that the subjects are confronted with items that indicate different levels of risk and are forced to evaluate them according to their subjective beliefs.

The operationalization of the risk concept becomes problematic when risk cannot be expressed in terms of monetary values. A typical measurement of risk, derived from the discipline of Finance, is the volatility of an asset, measured through the standard deviation of the returns or price of the asset (Besley [1999], Brigham [2002]). In this particular context standard deviation seems to be an inappropriate measure for the purpose of evaluating the individual's risk-taking preference due to the fact that it is a highly abstract measure that requires substantial knowledge and understanding of statistics and finance. For developing this tool we assumed that individuals have a limited amount of knowledge regarding the stock market and other forms of investments. The ideal form of the items would be a knowledge free assessment of risk-taking that allows the construction of an individual's risk-aversion score regardless of the background of the individual.

Scale Development

The development of the instrument was begun by examining the existing literature on risk-aversion and the measurement of the concept (Evans, Holcomb and Chittenden [1989], J. Grable and Lytton [1999], J. E. Grable [2000], Snelbecker, Roszkowski and Cutler [1990]). We reformulated some of the items obtained from these studies so that they could be used in the context of financial risk-taking and added several items to the pool. Chosen items were assigned to either the risk control or speculative risk dimension. For reasons previously discussed, all items that were obtained that included monetary amounts were disregarded. Another concern was that items be free of complicated terminology requiring finance specific knowledge. We discarded all items that included terminology that was not considered to be of average reading level.

The initial item pool included 20 items. An item format of the 5-option Likert-Scale with the options of Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree, and Strongly Agree was chosen. This format allowed the subjects to express their agreement with the items and at the same time measure various levels of the traits.

In the first study, we examined the statistical properties of the scale as well as investigated its predictive validity.

Methods

Participants

The 272 participants were students in a Finance class that is a requirement to obtain a major in Business at a mid-sized state university in the Midwestern United States. The class was an introductory level class covering the basic principles in the area of Finance. The sample consisted of 0.8% Freshmen, 6.8% Sophomores, 66.4% Juniors, and 25.4% Seniors. 38.1% of the sample was female and 61.9% was male. The mean age was 21.34 years.

The instrument was handed out as part of a longer questionnaire that covered financial investment decision-making as an in class activity at the middle of the semester. The middle of the semester was purposefully selected to ensure that the participants were educated and familiar with the terminology that was used to create the validation items. Participation in the study was voluntarily.

Analysis Plan

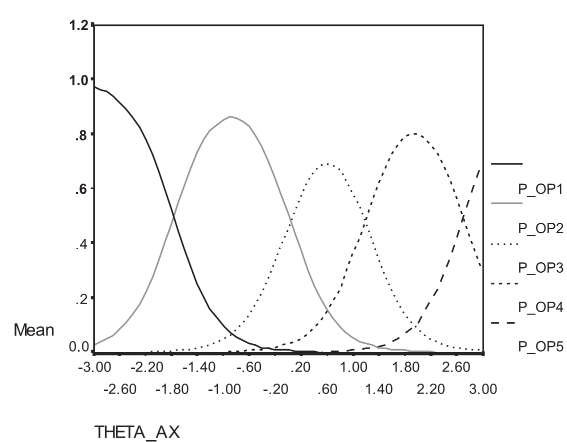
We conducted a tradition classical test theory (CTT) analysis of the reliability of the scales. The limitation of this approach is the fact that reliability is dependent on the sample; if the calibration sample is different from the operational sample, the psychometric properties of the test may change. Therefore the difficulty lies in the calibration of the sample; the subpopulation selected must represent the population for which the test is developed. Also traditional scale development techniques focus on the whole scale as the unit of analysis. For example, measurement precision or reliability is assumed to have one value for the entire scale and scores throughout the range of scores are assumed to have equal precision under typical CTT assumptions. This assumption of equal precision is implausible because items of scales differ in both level of precision and the location of precision.

A relatively new approach to overcome these drawbacks is Item Response Theory (IRT). The capability of IRT to examine the full range of a particular trait or ability is especially important for our risk-aversion scale because it may be possible that certain items are particularly good at measuring risk control or speculative risk at one or the other extreme of the spectrum.

Another advantage of IRT is that item-level statistics are easier to interpret than CTT statistics. For example, item-total correlations, the CTT index of the discriminating power of an item, are conflated with the item endorsement rate (often called item difficulty). Items with extremely high or extremely low endorsement rates will have low item-total correlations, regardless of the discriminating power of the item. IRT untangles difficulty and discrimination parameter estimates so that they can be more psychologically interpretable. Also IRT statistics are considered to be sample independent due to the estimating procedure in which three parameters, the option threshold levels of the items, the discriminating power of the items, and the latent trait level of the individuals, are simultaneously estimated. A final advantage relevant to this analysis is that IRT is able to pinpoint the level of information that each item is contributing to the scale. Information is related to the measurement precision each item or scale provides in understanding an individual's score on the psychometric construct. Information can be effectively used to eliminate items with low information values that seem not to contribute much information to the scale.

The option response function (ORF) is the foundation of item response theory when applied to items with more than two response options (i.e., polytomous), such as the items in the risk control and speculative risk scales analyzed in this paper. The ORF is a nonlinear function that relates the probability of choosing a particular response option as a function of the latent trait of speculative risk or risk control (e.g. see Figure 3). Therefore, for an item that has five response options, there will be five ORFs that correspond to each of that item's five options. Examining item 8, one item of the speculative risk scale ("I like to seek thrills in having high returns on my investment."); it is possible to compute the probability that an individual with a certain value of speculative risk would choose a specific option. For example in reference to Figure 3, a person with a speculative risk score of –1.0 (i.e., 1 standard deviation below the mean) should choose options 1 ("strongly disagree") less than 10 % of the time and option 3 ("Neither Agree or Disagree") less than 6 % of the time, option 2 ("Disagree") nearly 85% of the time.

FIGURE 3
ORF: Question Item 8, Factor 1: Speculative Risk



A person with this speculative risk score would choose options 4 and 5 very infrequently. For more background details on IRT, the reader is referred to Embretson & Reise [2000],"Essays on Item Response Theory."In Anne Boomsma, Marijtje A.J. van Duijn, Tom A.B. Snijders, eds. [2001],"Handbook of Modern Item Response Theory,"Wim J. van der Linden and Ronald K. Hambleton, eds. [1997], Zickar [1998, 2001, 2002].

Samejima's Graded Response Model (GRM)

The most widely used IRT model for ordered (e.g., Likert) data is the graded response model (GRM) developed by Samejima [1969]. Two different types of item parameters are estimated with the GRM. The *a* parameter determines the slope of the ORFs. Larger *a* parameters denote more discriminating items. Thus, an item with an a_i parameter of 2.0 will better distinguish between high and low speculative risk orientation or high and low risk control orientation than an item with an *a* parameter of 0.5. The *b* parameters are called option thresholds, which relate to how likely it is that individuals will endorse the option. Large, positive thresholds indicate that only individuals with a high value on the latent trait will tend to select options that correspond to the threshold. Thus, an option with a *b* parameter of +3.0 will probably only be endorsed by individuals with extreme speculative risk or extreme risk control orientations. Under the GRM, k-1 threshold parameters are estimated for an item with *k* options. MULTILOG 6.0 (Thissen [1991]) was used to estimate Samejima's GRM item parameters for both the risk control and speculative risk scales. All default options were used in MULTILOG.

Stability of the Scale

The 20-item questionnaire was re-administered to the initial sample after 12 weeks. This was undertaken to test the reliability of the measure and the feedback loop of the model. It was hypothesized that overall risk-aversion scores correlated highly and that the individuals had modified their perception of risk and moved toward the Risk Managing Investor. We assumed that the uncertainty concerning the stock-market along with the continuous exposure to the concept of risk and its consequences for the investor during class time increased the students' awareness of the concept and would cause this shift to occur.

Validity of the Scales

To develop validity evidence, participants were asked to rate themselves according to the following question, "When I have to make decisions regarding investing money I would describe myself as a person that:" The available choices were: 'Always takes risks', 'Takes risks more often', 'Sometimes takes risks', 'Takes and avoids risks evenly', 'Takes risks rarely', 'Avoids risks', and 'Never takes risks'. It was assumed that individuals are able to subjectively rate their overall tendency as being risk seekers or risk avers, and therefore a significant correlation between the self-rating and the risk-aversion scale was expected. This subjective rating can unfortunately not be used as a good indicator of risk-taking due to the fact that individuals seem to be biased when asked for self-evaluations. Men and young adults typically tend to overrate their risk-taking behavior whereas women and older individuals tend to underrate their risk-taking behavior (Powell & Ansic [1997]). Regardless, we thought this would be an important first step.

Another way of validating the scale is to test its ability to duplicate relationships revealed by previous research. One consistent finding of all reviewed research was that men display higher levels of risk-taking than women (J. E. Grable [2000], Powell and Ansic [1997]). It was expected that the risk-aversion scale would be consistent with the existing research.

To further validate the created scales the individuals were asked to allocate money to a range of investment options. First a scenario was created where the individuals were supposed to consider themselves as being financial advisors to some of their friends that had inherited $100,000. Here four different scenarios were described where the individual investment-needs of their friends were explained in form of a short scenario. The scenarios indicated that each of the hypothetical friends had differing financial needs. The subjects had to make a separate recommendation for each friend and create the ideal portfolio by allocating percentages to each of the available six investment options. The investment options were: stock market investments, short-term government bonds, long-term government bonds, short-term corporate bonds, long-term corporate bonds, and a savings account. We hypothesized that this would result in different investment recommendations for each scenario due to the existence of ideal theoretical solutions prescribed by financial theory independent of the individuals risk-aversion score. This hypothesis was based on the assumption that rational arguments induced by the scenarios would be considered when asked to select investment strategies for others rather than personal risk-taking preferences.

As next item the subjects were then asked to assume that they themselves had inherited $100,000 and were thinking about investing. They were given the same investment options as above and were asked to create their own portfolio by allocating percentages. The hypothesis was that the allocations should be influenced by the individual's risk-taking preference, where individuals with high scores on the risk-aversion scale should prefer the savings account and individuals with low scores should prefer the stock investments.

Testing the Model

The validation of the model involved two different procedures. In the first analysis the model was tested in regards to its ability of classifying individuals according to Figure 2 as Conservative Investors (CI), Risk Managing Investors (RMI), Speculators (S), and Non-Investors (N-I). To validate this property the subjects were classified as members of one of the above-mentioned groups through individual portfolio preferences using data from a modified questionnaire. The resulting groups were then used as the dependent variable in a discriminant analysis with speculative risk and risk control as independent variables. Discriminant analysis was selected due to its usefulness in situations in which a model of group membership based on observed characteristics of each case needs to be evaluated. The procedure generates a set of discriminant functions based on linear combinations of the independent variables that provide the best discrimination between the groups. The functions are generated from a sample of cases for which group membership is known. The traditional usage of discriminant analysis is to apply the generated functions to new cases with measurements for the independent variables but unknown group membership; here discriminant analysis was used with a different intention, namely as a confirmatory analysis in which its purpose was to confirm the model and its ability to classify individuals into one of the four quadrants according to their scores on the two scales.

In a second analysis the model was tested using structural equation modeling (SEM) to verify the impact of speculative risk and risk control on the risk-taking behavior. This approach to validate models has lately become popular in social sciences due to its ability to analyze latent traits as part of a model. The method uses the covariance matrix of the dataset to fit the data to a predefined model. The path coefficients will then allow inferences regarding the validity of the theorized model.

For the model validation analysis a different sample was used to avoid capitalizing on chance. Also the original questionnaire was amended to allow for the classification of the subjects into the four hypothesized categories.

Operationalization of the Classification of Subjects into the Hypothesized Categories

To classify the individuals, four portfolios were developed that suited one and only one category. The portfolios for the various investors included one with a 34% Cash, 33% Treasury Bonds, and 33% Corporate Bonds (low risk) mix for the CI, one 10% Cash, 30% Stock market U.S., 25% Stock market international, 20% Corporate Bonds, and 15% Government securities mix for the RMI, one 30% Stock market U.S., 40% Stock market international, 20% Emerging markets, and 10% Options mix for the S, and a 60% Cash, and 40% Government Securities mix for the N-I. The individuals were then offered four pairs of portfolio combinations and asked to select the preferred portfolio for each option. The classification of the individuals was based on the assumption that individuals obey the axiom of transitivity when making investment decisions. The transitivity axiom in general predicts that individuals that prefer Portfolio A over B and B over C have to prefer A over C. To meet the criteria of transitivity in this particular situation it was hypothesized that particular selections were made by the various groups; only individuals that endorsed the portfolio combinations accordingly were included in the analysis.

Scoring and Properties of the Scales

When developing a scoring scale for a test the procedure should be simplified as much as possible to allow for easy administration of the tool. A common procedure, here called ‘additive procedure’, used for scoring is to calculate the sum of the Likert-Scale answers of the individual, coded as Strongly Disagree = 1, Disagree = 2, Neither Agree nor Disagree = 3, Agree = 4, and Strongly Agree = 5. The resulting scale-score for speculative risk is then subtracted from the resulting risk control scale to obtain the risk-aversion scale. The higher the individual scores on the obtained risk-aversion scale the more risk aversion regarding financial investments the subject will display, risk seekers therefore score low and risk averters score high on the scale. The fact that IRT was used allows for a more sophisticated scoring procedure, here called ‘ORF scoring procedure’, due to the fact that the analysis reveals exact data about the location on the theta continuum of each response option for each item. The maximum of each ORF identifies the theta at which the individual’s trait is located. The sum of the individual’s thetas, indicated by the Likert Scale choice, specifies the trait level of the individual. The ORFs were analyzed and the theta for each Likert Scale option was obtained. Each subject’s speculative risk score as well as the risk control score was obtained by adding the thetas that resembled the individuals Likert Scale choice. The resulting speculative risk score was then subtracted from the risk control score. The interpretation of the resulting risk-aversion score is identical to the interpretations of the risk-aversion score that was obtained above. Whereas this procedure requires a considerable amount or time and the likelihood of scoring errors, due to human error, increases it is necessary to deter-

Table 1. *Scale Items with Factor Loadings*

Item:		Factor 1	Factor 2
Speculative Risk			
8)	I like to seek thrills in having high returns on investments.	.64	~0
13)	I see risk as an opportunity to make money.	.61	–.21
15)	For my personal investments I prefer stocks that have undergone significant fluctuations in Price during the last 6-months because then there is potential for a high return on the investment.	.46	~0
16)	I get a thrill out of investing.	.58	–.25
17)	When I invest money a high return on my investment, even though it means accepting a high degree of risk, is the most important aspect.	.61	~0
Risk Control			
1)	When I invest money a safe return is very important to me.	–.16	.71
3)	I prefer putting money into a bank account because then I know exactly how much money I will have in the future.	–.23	.63
6)	When I invest money I want to be in control regarding the return.	.16	.58
12)	It is important to know with how much money my investment will provide me in the future.	~0	.58
20)	When I invest I plan on having a specific amount at a future date.	~0	.45

mined whether the results are worth the effort. For an evaluation of the results see section: Scoring and Properties of the Scale below.

Results

Item Analysis

In a first step, all 20 items were subjected to a two factor principal axis factoring analysis (PAF) with a Varimax rotation and Kaiser normalization. For the initial analysis, the first two factors explained 27 % of the variance; other factors explained trivial amounts. Items 2, 4, 5, 7, 10, 11, 18, and 19 with high cross loadings were eliminated to ensure the distinguishability of the two scales. The remaining 12 items were reanalyzed and revealed an explained variance of 33.84 % with high discrimination between the two factors. The item loadings for the final 10 items (rational for the exclusion of items 9 and 14 see discussion below) are detailed in Table 1.

As predicted, two factors explained the dataset appropriately. Bartlett's test of Sphericity was highly significant with a high Chi-Square value of 685.22 indicating that the correlations of the variables in the population were different from zero. The Kaiser Meyer Olkin measure, summarizing the partial correlations of the Anti Image Correlations matrix, indicated that the variables were appropriate for the usage of a factor analysis (KMO = .77) (Kaiser [1974]). The measures of sampling adequacy (MSA) were between .70 and .84 for all variables, confirming a good fit of the model as well.

Results of the IRT Analysis

Next, the items were subjected to an IRT analysis. The a_i and b_i item parameters were estimated by MULTILOG, see Table 2. The ORFs indicated that the items for speculative risk (Items 8, 13, 15, 16, 17) mea-

Table 2. *Estimated Parameters*

Items			a	b_1	b_2	b_3	b_4
Factor 1							
Speculative Risk	8)	Estimate (S.E.)	1.70 (0.23)	–1.77 (0.23)	0.02 (0.12)	1.20 (0.18)	2.72 (0.40)
	9)	Estimate (S.E.)	0.72 (0.16)	–4.53 (0.94)	–0.93 (0.32)	0.35 (0.27)	2.22 (0.58)
	13)	Estimate (S.E.)	1.49 (0.19)	–1.48 (0.24)	0.37 (0.14)	1.62 (0.23)	3.84 (0.74)
	14)	Estimate (S.E.)	0.82 (0.16)	–3.38 (0.77)	0.21 (0.23)	2.98 (0.60)	4.99 (1.14)
	15)	Estimate (S.E.)	1.01 (0.18)	–4.44 (0.84)	–1.44 (0.30)	0.58 (0.22)	2.74 (0.53)
	16)	Estimate (S.E.)	1.50 (0.18)	–2.01 (0.30)	–0.67 (0.16)	1.17 (0.19)	2.64 (0.41)
	17)	Estimate (S.E.)	1.63 (0.20)	–2.69 (0.38)	–0.60 (0.14)	0.62 (0.15)	2.53 (0.37)
Factor 2							
Risk Control	1)	Estimate (S.E.)	2.59 (0.33)	–2.52 (0.31)	–1.82 (0.17)	–1.25 (0.12)	0.69 (0.10)
	3)	Estimate (S.E.)	1.61 (0.19)	–2.10 (0.27)	–0.86 (0.14)	0.04 (0.12)	1.55 (0.20)
	6)	Estimate (S.E.)	1.30 (0.18)	–7.07 (****)	–2.56 (0.83)	–0.61 (0.21)	1.95 (0.59)
	12)	Estimate (S.E.)	1.25 (0.20)	–4.14 (0.82)	–2.20 (0.33)	–1.22 (0.20)	1.28 (0.22)
	20)	Estimate (S.E.)	0.89 (0.17)	–4.63 (1.04)	–2.00 (0.40)	–0.49 (0.20)	2.82 (0.52)

sure the trait across the whole continuum efficiently. This can be inferred from the ORF curve locations that are evenly distributed across the theta-continuum. Items 9 and 14 had low a_i parameters indicating that they did not add much information (see Table 2) to the scale and were therefore dropped. The low discriminating power can exemplary be seen for Item 14 in Figure 4. The remaining items all contributed a considerable amount of information, leading to the inclusion of five items for the speculative risk scale.

For the items covering risk control (Items 1, 3, 6, 12, 20) items 1 and 12 had higher discriminating power in the lower portion of the theta-continuum, exemplary see Figure 5. The remaining items had equally distributed discriminating power, leading to five items for the risk control scale.

The fit of the model was confirmed by comparing expected probabilities of endorsements to observed probabilities of endorsements. For most items the expected and observed probabilities were identical, for a few the differences in the probabilities was 0.01, indicating good model fit. In addition the GRM fit all items acceptably using a chi-square evaluation procedure developed by Drasgow, Levine, Tsien, Williams, et. al. [1995]. The total information functions indicated that the two scales discriminated roughly equally across the continuum.

Cronbach's alpha was calculated on the remaining 5 items for speculative risk ($\alpha = .73$) and on the 5 items remaining from the risk control scale ($\alpha = .73$), indicating that there was reasonable internal consistency, given the few items.

Stability of the Scales

The questionnaire was re-administered to a group that originally consisted of 149 individuals 12 weeks after the initial administration with a response rate of 68.4 %. The correlation for the dimension speculative risk was .57 ($p < .001$), for the dimension risk control .58 ($p < .001$), and .74 ($p < .001$) for the overall risk-aversion scale. These reliabilities were acceptable given the 12-week lag between the two administrations, especially for the overall scale. According to the hypothesized model the individuals should have maintained their overall risk preference (total risk-aversion score should not have changed) but the individuals should have moved from quadrant I, III, or IV to quadrant II (Risk Managing Investor). This movement is predicted by the feedback loop that indicates that individuals are influenced by personal experience and knowledge regarding risk management.

Throughout the 12 weeks between test and retest our subjects were exposed to a volatile stock market and numerous in-class discussions regarding financial investments, the associated risk and proper risk management. The Dow Jones Industrial Average Index for example, while overall maintaining an average of 10121.74 underwent large fluctuations with a high of 10635.25 and a low of 9618.24. We assumed that this exposure should have had some influence on the individuals' risk-taking behavior but this was not backed up by the scale statistics. The speculative risk score's mean was 15.37 with 3.64 as standard deviation for the first questionnaire and a mean of 15.58 and standard deviation of 3.21 for the retest. Risk control had a mean of 18.53 and 3.45 standard deviation and a re-test mean of 18.60 with a standard deviation of 3.00. Dependent groups' t-tests were not significant on either subscale. Regardless of the findings we still believe that the feedback loop should be included in the model but further research is necessary to confirm and validate its influence on the individuals' risk-taking behavior.

FIGURE 4
Excluded ORF: Question Item 14, Factor 1: Speculative Risk

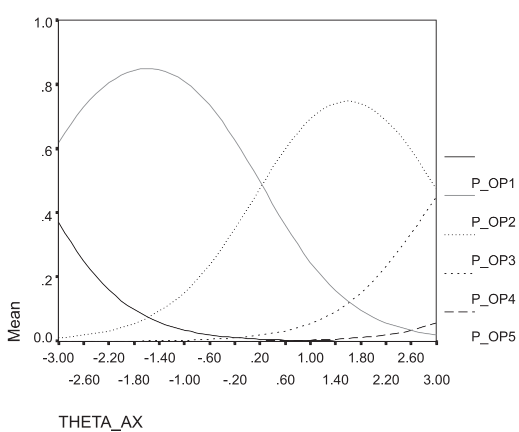
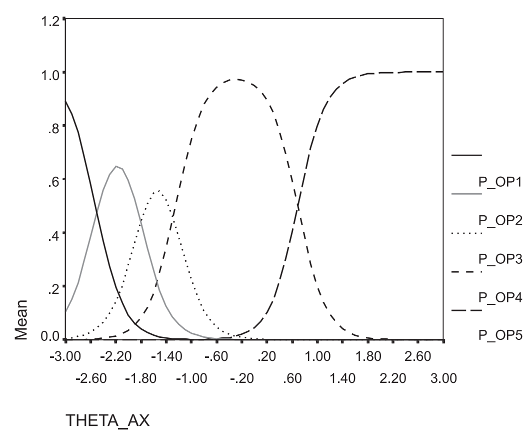


FIGURE 5
ORF: Question Item 1, Factor 2: Risk Control



Validity of the Scale

The correlation of the subjective rating and the risk-aversion scale was significant ($p < .001$) with $r = .47$, indicating that the scale measured risk-aversion. In addition, a highly significant t-test ($p < .001$) with gender as grouping variable revealed that men and women had different scores on the risk-aversion scale with a mean of 1.58 and 4.02 respectively, indicating that women were more risk avers than men. These findings were consistent with previous research (J. E. Grable [2000] and Powell and Ansic [1997]).

Regarding the creation of portfolios for others, the significant correlations between the individual's risk-aversion score and the various allocations suggested that the individual risk-taking preference had some influence on the portfolio selection. The magnitude of the correlations, between |.14| and |.26|, indicated that the individual's risk-taking preference had some influence on the recommended investment strategies. Contrary to our postulate this influence existed but can be considered minuscule especially when compared to the magnitude of the influence observed for the individual's portfolio selection (as explained below). An explanation could be that subjects did not use financial theory exclusively to make their recommendations but let individual biases influence their decisions.

Regarding the creation of the subject's own portfolio the correlations between the risk-aversion score and the percentages allocated to various investments indicated that there was a strong relationship between the actual risk-taking behavior and the developed scale. The results were impressive due to the fact that there was a strong correlation between the risk-aversion scale and the amount allocated to the stock market, the investment option with the highest risk. The statistics illustrated that there was a highly significant ($p < .001$) correlation ($r = -.55$) indicating that the higher the individual scored on the risk-aversion scale the lower was the amount allocated to the stock investment. In addition, there was a significant ($p < .001$) correlation ($r = .42$) between the risk-aversion scale and the allocation to the Savings account, a rather safe investment. This indicated that risk avers investors allocated a larger amount of there money to safe investments such as savings accounts. Overall the mean and median of the stock allocation was 27.21 and 25.00 respectively with a standard deviation of 19.92. The allocations for the savings account had a mean of 26.93, a median of 20.00, and a standard deviation of 23.66. Further confirming our hypothesis there was also a highly significant ($p < .001$) correlation ($r = .23$) between the risk-aversion scale and long-term government bonds, a rather safe investment, and a significant ($p < .01$) correlation ($r = .18$) between the risk-aversion scale and long-term corporate bonds. The difference in magnitude of the correlations can be explained by the fact that long-term corporate bonds are generally considered to be an investment of higher risk then long-term government bonds. The allocations for the long-term government bond option had a mean of 18.68, a median of 20.00, and a standard deviation of 13.99. The allocations for the long-term corporate bond had a mean of 12.91, a median of 10.00, and a standard deviation of 10.95.

The correlations between the risk-aversion scale and the short-term government bonds and short-term corporate bonds were very low and not significant. The frequency table revealed that 45.6 % of the individuals allocated 0 % to the short-term government bond and 43 % allocated 0 % to the long short-term corporate bond option. Overall the allocations for the short-term government bond had a mean of 7.25, a median of 5.00, and a standard deviation of 9.55. The allocations for the short-term corporate bond had a mean of 7.00, a median of 5.00, and a standard deviation of 8.40, indicating that most subjects did not perceive the short-term investments as valuable additions to their portfolios.

The above-described correlations indicated that there was high content and construct validity of the developed risk-aversion scale.

Validity of the Model

Administration of the Instrument

The modified questionnaire was handed out to a group of students with no overlap to the previously used sample that were in the process of pursuing a Bachelor of Science / Arts in the area of Business with a specialization in Finance. The questionnaire was administered at the end of the semester to ensure that the participants were educated and had been exposed to the material of the courses. The participation in the study was voluntarily; the response rate was 22%.

Participants

The 88 participants of this study consisted of 1.1% Freshmen, 45.5% Sophomores, 33% Juniors, and 20.5% Seniors. The mean age was 22.10 years, 44.3% of the subjects were female, 55.7% were male. Of the 88 participants 44.3% had at least one or more years of experience with financial investments.

Discriminant Analysis: Categorizing Properties of the Model

Classification of Subjects

The data revealed that 87.5% of all participants made transitive decisions and were therefore included

Table 3. *Hypothesized Portfolio Preferences*

	Portfolio			
Group	**CI vs. RMI**	**RMI vs. S**	**S vs. N-I**	**N-I vs. CI**
CI	CI	RMI	N-I	CI
RMI	RMI	RMI	S or N-I	CI
S	RMI	S	S	CI
N-I	CI	RMI	N-I	N-I

in the analysis. The categorization according to Table 3 lead to the following distribution: Conservative Investor 11.4%, Risk Managing Investor 51.1%, Speculator 18.2%, Non-Investor 6.8%.

Discriminant Analysis

The discriminant analysis using the groups obtained by the objective portfolio selection as dependent variable and speculative risk and risk control as independent variables revealed that the group means on the speculative risk and risk control dimension differed as displayed in Table 4. Wilks' Lambda was highly significant for speculative risk ($p < .001$) and for risk control ($p < .01$). The test of equality of group means indicated that the means of the groups were not the same. The Box's M test statistic approximating an F-statistic was not significant ($p = .67$), indicating that the assumption of homogeneity of the covariance matrixes necessary for mean comparisons was satisfied. The Eigenvalues of the canonical discriminant functions were .61 for function 1 and .03 for function 2, indicating that they explained 95.9% and 4.1% respectively of the variance. Both discriminant functions were included in the analysis due to Wilks' Lambda where the Chi-square was highly significant ($p < .001$) for both equations. This second appearance of Wilks' Lambda serves a different purpose than in the above-mentioned context, here it tests the significance of the Eigenvalues for each

Table 4. *Group Statistics According to Portfolio Selection*

Group	Mean	Standard Deviation	N
CI			
Speculative Risk	13.00	2.98	10
Risk Control	20.60	3.41	10
RMI			
Speculative Risk	16.48	3.28	45
Risk Control	18.03	3.19	45
S			
Speculative Risk	20.23	2.95	16
Risk Control	16.69	2.96	16
N-I			
Speculative Risk	15.50	1.76	6
Risk Control	20.50	3.02	6
Total			
Speculative Risk	16.73	3.71	77
Risk Control	18.28	3.36	77

discriminant function, where the resulting discriminant functions are orthogonal.

Fisher's linear discriminant functions of the unstandardized discriminant coefficients indicated that, as predicted, CI had low coefficients on speculative risk and high coefficients on risk control, RMI had high coefficients on both dimensions, S had high coefficients on speculative risk and low coefficients on risk control, and N-I had low coefficients on speculative risk and high coefficients on risk control, compare Table 5.

The classification table indicated that the hit ratio (correct classifications in percent) was 30% for CIs, 88.9% for RMIs, 56.3% for Ss, and 0% for N-Is. The overall percentage of correct classifications was 67.5%. The results are graphically depicted in Figure 6, indicating that speculative risk and risk control serve as classifiers of the group.

This result contributed to the validation of the model and its structural components. It indicated that individuals could be classified in the hypothesized groups and that the factors speculative risk and risk control measured the hypothesized dimensions.

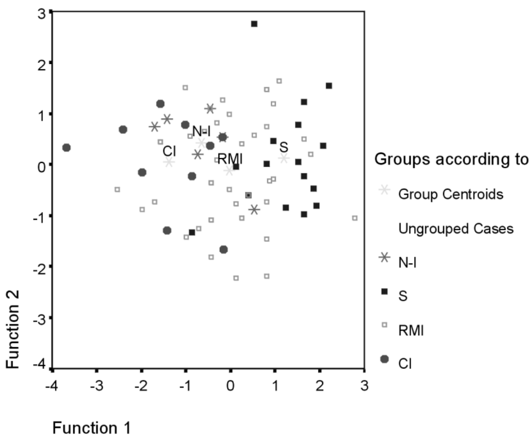
Structural Equation Modeling

The model was a recursive model with two exogenous latent variables, speculative risk (SR) and risk control (RC), and one endogenous latent variable, risk-taking (RT). The latent variables were measured through various manifest variables, SR was defined through question items 8, 13, 15, 16, and 17, RC was defined through question items 1, 3, 6, 12 and 20, RT was defined through the subjective rating by the individuals regarding their risk-taking (SRISK) and the individuals personal portfolio allocations as illustrated in section: Validity of the Scales. STOCK measured the allocation to the stock market, s-t GB the allocation to the short-term government bond, l-t GB the allocation to the long-term government bond, s-t CB the allocation to the short-term corporate bond, l-t CB the allocation to the long-term corporate bond, and SAVING the allocation to the savings account, all allocations were in percent. The structural equations were SR $\rightarrow$ RT and RC $\rightarrow$ RT, SR and RC were uncorrelated, all error variances were initially assumed to be independent, but modification indexes indicated that the error of the portfolio allocations should covary. We included these covariances in the model because they could be inter-

Table 5. *Fisher's Linear Discriminant Functions*

	Groups According to Portfolio Selection			
Dimension	**CI**	**RMI**	**S**	**N-I**
Speculative Risk	1.50	1.85	2.23	1.76
Risk Control	2.16	1.92	1.81	2.16
(Constant)	–34.00	–33.08	–39.26	–38.37

FIGURE 6
Canonical Discriminant Functions



preted as indications of other factors besides RT, which were not measured by the model but influenced the allocations.

Dataset

The dataset was obtained from a second questionnaire and contained 71 observations after missing values had been excluded listwise. To meet the assumption of multivariate normality the variables concerning the portfolio allocations of the individuals, containing many zeros and therefore poison distributed, had to be transformed. The power-transformation $y = (x_i + 0.5)^{.01}$ was used. This led to an approximate normal distributed dataset.

Model Fit

The model had 101 degrees of freedom with a chi-square of 123.72 and a p-value of 0.062; indicating that the model fit the dataset fairly well. The estimated Non-centrality Parameter (NCP) was 22.72 with a 90 percent confidence interval for the NCP of 0.0 to 55.02, the NCP was regarded as being fairly low further indicating good fit.

The root mean square error of approximation (RMSEA) was 0.057 with a 90 percent confidence interval ranging from 0.0 to 0.088 with a p-value of .36 for a test of close fit (RMSEA < 0.05) indicating reasonable fit. The expected cross-validation index (ECVI) was 3.25 for the hypothesized model with a 90 percent confidence interval for the ECVI of 2.93 to 3.71, an ECVI for the saturated model of 4.37, and an ECVI for the independence model of 7.20 indicating that the hypothesized model had the best fit compared to the two other models.

The comparative fit index (CFI = 0.86), and incremental fit index (IFI = 0.88) are evaluated according to their closeness to 1. A value larger .9 is considered as good fit, values close to .9 are considered as mediocre fit. The values were fairly close to .9, indicating mediocre relative fit compared to the independence model. The root mean square residual (RMR = 0.067) and the goodness of fit index (GFI) of 0.83 indicated mediocre absolute fit.

In conclusion the fit indices indicated that the model had reasonable fit statistics and was therefore treated as reliable when interpreting the estimated coefficients.

Model Estimates

The model estimates were derived using the maximum likelihood estimating procedure. The measurement model for SR indicated that the items 8, 13, 15, 16, 17 defined the construct fairly well. The estimated coefficients were high with low standard errors and high t-values, all highly significant, see Table 6. The same applied to RC, where items 1, 3, 6, 12, 20 described the construct with high path coefficients and highly significant t-values. The estimated measurement errors are depicted in Figure 7, with low standard errors and highly significant t-values. The squared multiple correlations for the x – variables indicated the amount of variance explained by the items. RT was measured by SRISK, STOCK, l-t CB, and SAVING, where the path coefficients were high and the t-values highly significant. For s-t GB, l-t GB, and s-t CB the t-values were not significant. This indicated that individuals did not differentiate between s-t government, l-t government and s-t corporate bonds, which was already alluded to in section: Validity of the Scale.

For interpretative purposes the standardized values were used allowing for comparison of the different measures. The standardized path coefficients were –0.69 from SR to RT and 0.46 from RC to RT with standard errors of 0.70 and 0.50 and highly significant t-values of –2.42 and 2.27 respectively, for all coefficients see Figure 7. The squared multiple correlation for the structural equation was 0.84 indicating that 84% of the variance was explained by the relationships of the model.

The path coefficients for the structural model indicated that SR and RC had opposite effects on RT, one was encouraging the other one was discouraging risk-taking, theses findings further contributed to the validity of the model that predicted this relationship. It also supported the procedure chosen to develop the risk-aversion measure where speculative risk was subtracted from risk control.

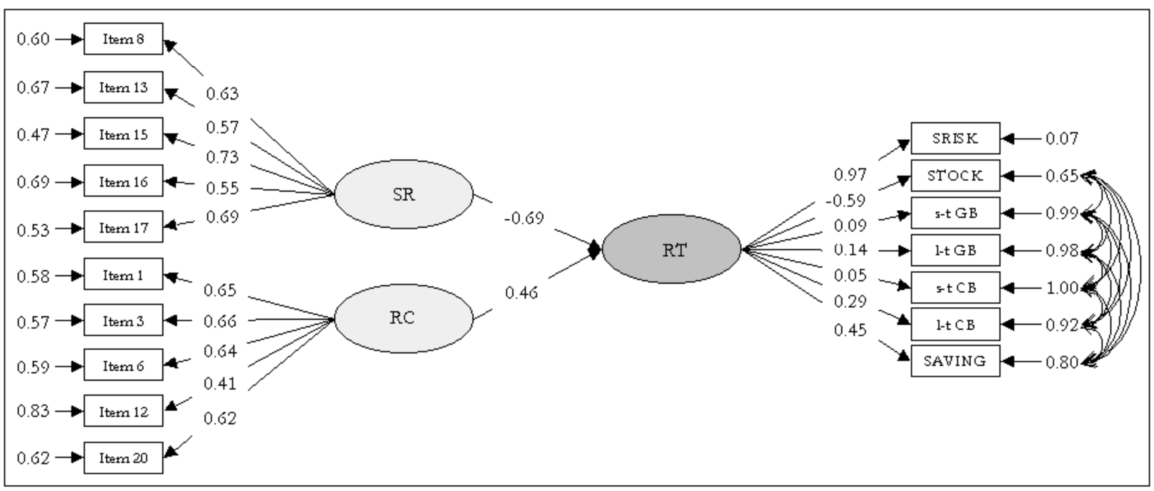
Scoring and Properties of the Scale

Statistics revealed that the correlation of the two resulting approaches to score the scales, the ‘additive procedure’ and the ‘ORF scoring procedure’, were

Table 6. *Lambda-X, Lambda-Y as well as the Squared Multiple Correlations for X, Y – Variables (SMC), Standardized (Sta.) and Unstandardized (Usta.)*

	SR		RC		RT				
Item	**Sta.**	**USta.**	**Sta.**	**USta.**	**Sta.**	**Usta.**	**SE**	**T-value**	**SMC**
1	- -	- -	0.65	0.51	- -	- -	0.09	5.44	0.42
3	- -	- -	0.66	0.88	- -	- -	0.16	5.52	0.43
6	- -	- -	0.64	0.52	- -	- -	0.10	5.32	0.41
8	0.63	0.74	- -	- -	- -	- -	0.13	5.47	0.40
12	- -	- -	0.41	0.34	- -	- -	0.11	3.22	0.17
13	0.57	0.55	- -	- -	- -	- -	0.11	4.85	0.33
15	0.73	0.77	- -	- -	- -	- -	0.12	6.56	0.53
16	0.55	0.54	- -	- -	- -	- -	0.12	4.65	0.31
17	0.69	0.70	- -	- -	- -	- -	0.12	6.08	0.47
20	- -	- -	0.62	0.65	- -	- -	0.13	5.13	0.38
SRISK	- -	- -	- -	- -	0.97	0.54	0.20	2.69	0.93
STOCK	- -	- -	- -	- -	–0.59	0.00	0.00	–2.89	0.35
s-t GB	- -	- -	- -	- -	0.09	0.00	0.00	0.68	0.01
l-t GB	- -	- -	- -	- -	0.14	0.00	0.00	1.11	0.02
s-t CB	- -	- -	- -	- -	0.05	0.00	0.00	0.43	0.00
l-t CB	- -	- -	- -	- -	0.29	0.00	0.00	1.98	0.08
SAVING	- -	- -	- -	- -	0.45	0.00	0.00	2.56	0.20

FIGURE 7
SEM Model with Standardized Estimates



highly significant (p < .001) with a correlation coefficient of .86 and .86 for speculative risk and risk control respectively. The two differently obtained risk-aversion scales correlated highly significant (p < .001) with a correlation coefficient of .97. The high correlation of the two procedures indicated that the simple ‘additive procedure’ approach of adding the Likert Scale scores generated similar results as the more complicated ‘ORF scoring procedure’ and is therefore sufficient to score the scale.

The resulting scales had the following properties. Speculative risk had a mean of 15.93 with a standard error of .20, median of 16.00, and standard deviation of 3.31. The range was 17.00 with a minimum of 7.00 and a maximum of 24.00. The skewness was –.05 with a kurtosis of –.30. For risk control the mean was 18.38 with a standard error of .19, median of 19.00 and a standard deviation of 3.07. The range was 16.00 with a minimum of 9.00 and a maximum of 25.00. The skewness was –.28 and –.06 kurtosis. The histogram, kurtosis and skewness measures indicated that the assumption of normality was met. The risk-aversion scale was normally distributed; the Shapiro-Wilk Test of Normality was not significant with a W of .994 and a p-value of .34. The risk-aversion scale had a mean of 2.45, a standard error of .32, and a standard deviation of 5.24. The median was at 2.00 and the range of the scale was 30.00 with a minimum of –12.00 and a maximum of 18.00, skewness was –.03, and kurtosis was .12.

Discussion

We think that the above discussed model as well as the inventory meets the required standards for consideration in further research. The statistical methods applied confirmed the model as well as the operationalization and the validation methods yielded impressive results.

Implicit assumption of the model is the supposition of the rational investor and thereby the claim that the investor will maximize his or her utility according to certain preferences. Once that assumption is relaxed and risk preferences, such as for example risk aversion, will not lead to a conservative investment decision the above research seems redundant. So far research indicates that individuals, although not completely following rational choice models, seem to try to maximize their utility based on rational choices. As long as this paradigm holds the above-discussed model offers a theoretical framework that allows for a classification of individuals in the postulated groups and a measurement of individual risk-aversion concerning financial investments.

Besides this fundamental assumption other details lead to caution in generalizing the results to a broad population. The sample, for instance, was primarily selected from a student population and should in future research be expanded to professionals and other groups. In addition to that, it could be argued that all subjects were business students and had some exposure to financial concepts as well as to risk discussions and were therefore so called 'experts'. This would imply that the results of the study could not be generalized to a broad population. The fact that these students were more similar to the typical investor, who has some but not too much knowledge about financial theory, could serve as a counterargument. In general we think that the results are somewhat representative but future research in various countries with different populations would clarify this dispute and is therefore necessary.

We are aware of the fact that for stable IRT and SEM results large sample sizes are required, but for the purpose of the development of a preliminary questionnaire a smaller sample size can be justified. In addition the IRT statistic indicated a very low standard error and was therefore considered as fairly stable. The SEM with a very small sample produced good interpretable results but here the sample size is much more of a problem. Typically for SEM a small sample size leads to the problem of having non-normal distributed data creating an unsolvable problem. Here the data was approximately normally distributed leading to interpretable results. Although acceptable this, as well as the previous paragraph, indicates the need for future research with a larger sample.

In addition it needs to be mentioned that other factors besides risk-taking influence portfolio allocations and should in future research be included in the SEM model to improve fit indices and further validate the model. Here the application of decision theory, overconfidence, and allocation of resources could be implemented as manifest variables and clarify issues that influence portfolio selection in addition to risk-taking preferences.

For future research the above-mentioned model with its operationalization could serves as variable in decision theory models to further clarify financial decision making and shed light on stock market or other investment decisions.

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