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A test of the relevant association between utility theory and subjective risk tolerance: Introducing the Profit-to-Willingness ratio

Wookjae Heo [a,*], John E. Grable [b], Abed G. Rabbani [c]

[a] South Dakota State University, United States
[b] University of Georgia, United States
[c] University of Missouri, United States

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ABSTRACT

The purpose of this study was to document the empirical linkage between an objective risk tolerance utility function and a subjective risk tolerance scale. This study utilized return data from 2008 through 2013 for the S&P 500 as a proxy for the objective risk tolerance utility function and risk tolerance data obtained from a multidimensional psychometrically designed financial risk tolerance scale. Results from this study add to the literature by introducing the Profit-to-Willingness ratio (P/W ratio) and by showing investments in the stock market exhibit strong associates with the risk attitudes and preferences of investors. It was determined that an increase in the S&P 500 was associated with a decrease in aggregate risk tolerance during the period of analysis, whereas a decrease in the index increased willingness to take financial risk during the same period.

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1. Background and research question

Investments in the stock market tend to be positively associated with the risk attitudes and preferences of market participants (Kumari and Mahakud, 2015). A fundamental aspect of modern portfolio theory is the notion that risk and returns are positively related and that elevated levels of risk are positively associated with higher expected profits when investments are made (Bodie et al., 2010; Markowitz, 1952). In other words, risk-aversion and its inverse, risk tolerance, are generally hypothesized to be strongly associated with investing behavior (Madura, 2014). There also appears to be a strong association between the concepts of risk aversion and risk tolerance and market volatility (Bali and Zhou, 2017; Kamstra et al., 2017; Michaelides and Zhang, 2017), with risk taking behavior being influenced by financial and social factors (Chao et al., 2017; Kirchler et al., 2017). This is the reason that researchers have, over the past half-decade, taken steps to better understand the relationship between risk aversion/tolerance and investment behavior (e.g., Bailey and Kinerson, 2005; Hanna and Chen, 1997; Hoffmann et al., 2013).

Based on a researcher's theoretical orientation and preferences, multiple tools and techniques to evaluate the association between risk aversion/tolerance and investment behavior have been used in the literature. Some researchers have relied on simple lottery scenarios that require test takers to choose from options with predetermined odds of success and failure (e.g., Abdellaoui et al., 2017; Amuedo-Dorantes and Pozo, 2002; Lusardi, 1998; Tversky and Kahneman, 1992). Responses to these types of questions are most often used to develop constant relative risk aversion estimates (Barsky et al., 1997). Others have taken the view that revealed preferences can be used as a proxy for risk tolerance (Holzmeister, 2017). Those who advocate this approach believe that gauging current and past choice behavior is predictive of future action.

Another group of researchers, primarily those informed by psychology and the science of psychometrics, have attempted to measure risk tolerance with standardized scales. This approach focuses on applying classical test theory in the development of valid and reliable measures. The use of statistical measures in quantifying the usefulness of scales makes these tools a favorite way to evaluate the willingness of individuals to take risk (Anderson et al., 2015). Two popular psychometrically developed scales are widely used by researchers (Ryack et al., 2016). The first is a commercial product marketed by FinaMetrica PTY Ltd. The FinaMetrica® scale consists of 25 items (see http://www.riskprofiling.com). The other scale is a publicly available measure developed by Grable and Lytton (Grable–Lytton). This brief measure consists of 13 items (Grable and Lytton, 1999). Both the FinaMetrica® and Grable–Lytton measures were designed to facilitate the estimation of someone's risk tolerance or a decision maker's willingness to engage in a risky financial behavior in which the outcome is both unknown and potentially negative. The resulting risk score can be used to match

* Correspondence to: Box 2275A / Wagner Hall 149, Brookings, SD 57007, United States.
E-mail address: wookjae.heo@sdstate.edu (W. Heo).

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investment products and/or portfolios to someone's investing preference. The Grable–Lytton scale has been checked for validity and reliability over extended periods of time (Grable and Lytton, 2001, 2003; Kuzniak et al., 2015). Although improvements in the scale have been suggested, the scale continues to be used by researchers, educators, and financial planning practitioners, primarily based on the scale's reliability ($\alpha \geq .70$).

The Grable–Lytton measure was designed to provide an estimate of a decision maker's subjective willingness to take financial risk. This can be, of course, different from a person's actual behavior (Grable, 2000; Roszkowski et al., 2005). This is the reason some researchers prefer to use revealed preference techniques and other economic measures of relative risk tolerance. Traditionally, there has been little overlap among approaches, which has resulted in researchers choosing one methodology as a preferred assessment technique while excluding other approaches. Methodological preference can often be explained by the ease to which an approach can be implemented. For example, traditional economic utility theory measures utility objectively using market information. Compared to the measurement of risk tolerance via scaling, the established economic technique offers a more econometrically elegant measurement.

In traditional economic theory, decision makers are assumed to act rationally in an attempt to maximize economic utility. However, actual investment behavior often varies in a way that is hard to explain using economic utility theory because actual investing behavior sometimes appears to be irrational or biased (Benartzi and Thaler, 2007). To account for apparent irrationality, Tversky and Kahneman (1992) adjusted elements of utility theory when they introduced prospect theory, which combined economic constructs with psychological perspectives. Tversky and Kahneman noted three major effects related to seemingly irrational behavior: (1) the certainty effect, (2) the reflection effect, and (3) the isolation effect. The certainty effect occurs when decision makers underestimate a probable outcome when compared to a certain outcome. The reflection effect describes the tendency of decision makers to be risk-averse when they expect a gain and risk-seeking when they expect a loss. The isolation effect occurs when decision makers do not consider sequential values and probability, but rather focus only on current observable values and probabilities. By introducing these three effects, Tversky and Kahneman helped explain why investors sometimes make what appear to be irrational decisions when formulating investment decisions.

Prospect theory, as introduced by Tversky and Kahneman (1992), provides a pathway to make a linkage between subjective risk tolerance measurements (e.g., Grable–Lytton scale) and objective observations from the market (e.g. utility equilibrium). Specifically, if it is assumed that prospect theory reflects an investor's psychological profile at the time a decision is made (in the context of a utility function), risk tolerance measured with a scaling tool, such as the Grable–Lytton scale, should be expected to be related to behavior.

Given this proposition, the research purpose of the current study was to identify an empirical linkage between an objective risk tolerance utility function and a subjective risk tolerance scale. Specifically, this study utilized return data from 2008 through 2013 for the S&P 500 and the Grable–Lytton scale. The S&P 500 was used as a proxy for the objective risk tolerance utility function, whereas the Grable–Lytton measure was used an indicator of a scaling methodology.

2. Risk tolerance expressed by the S&P 500

Based on an economic utility function with a prospect theory adjustment, the risk tolerance utility function can be written as function (1) and (2):

$$\text{When gain case, } U(x) = 1 - e^{-x/R} \tag{1}$$

$$\text{When loss case, } U(x) = 1 - e^{x/R} \tag{2}$$

where, $U(x)$ denotes utility from investment; x denotes the net-profit; and R denotes the dollar amount that an investor must endure.

If it is assumed that individual investors should pay the current price of the S&P 500 index, the index can be considered to be the basic investment fund for investors. This leads to two additional assumptions:

(a) The current S&P 500 price represents an amount that an investor is willing to risk (e.g., same as the purchasing price at the first investment); and
(b) The change in S&P 500 price (Current S&P 500-Past S&P 500) represents a net profit (e.g., same as the gain or loss from the investment).

By (a) and (b), the exponent of the utility function (i.e., $-x/R$ and x/R) implies what is termed the Profit-to-Willingness ratio (P/W ratio) in this study. The profit can be positive (i.e., gain) or negative (e.g., loss). Based on the above assumptions, it is possible to write the exponents as equations with the S&P 500 index as functions (3) and (4):

$$\pm \mathrm{x/R} \fallingdotseq \pm\alpha^{*}\mathrm{P/W\ Ratio}$$

$$U(x) = 1 - e^{-\alpha^{*}\mathrm{P/W\ Ratio}}, \text{ when S\&P 500 is gaining} \tag{3}$$

$$U(x) = 1 - e^{\alpha^{*}\mathrm{P/W\ Ratio}}, \text{ when S\&P 500 is losing} \tag{4}$$

where, α denotes the constant value that makes the Percentage Change to match with x/R.

3. Objective risk tolerance linked to a risk tolerance scale

In addition to the assumption that risk tolerance can be expressed using the S&P 500 index, another assumption is needed. Specifically, a psychometrically derived risk tolerance score can be correlated with the S&P 500 index. In this study, such a score was measured by the Grable–Lytton scale. If the concept of a P/W ratio (i.e., x/R) is proportional to measured risk tolerance, it is reasonable to hypothesize that the P/W ratio can be used as an indicator of a risk tolerance score, as shown in Eq. (5).

$$\pm \mathrm{x/R} \fallingdotseq \pm\alpha^{*}\mathrm{P/W\ Ratio} = \gamma^{*}\mathrm{RiskToleranceScore} \tag{5}$$

where, γ denotes the certain value that makes the Risk Tolerance Score match to the P/W ratio.

This study tested Eq. (5) using empirical data from the S&P 500 index and the Grable–Lytton scale. A time-series regression analysis was utilized to verify the equation. For testing purposes, the equation for evaluating the association between the P/W ratio and risk tolerance scores was changed as follows (Eq. (6)):

$$\begin{aligned}&\alpha^{*}\mathrm{P/W\ ratio}\\ &\quad = \alpha^{*}[(\text{Current S\&P 500-Past S\&P 500})/\text{Current S\&P 500}]\\ &\quad = \gamma^{*}\mathrm{RiskToleranceScore}.\end{aligned} \tag{6}$$

The difference between the current S&P 500 index and the past S&P 500 index was assumed to be the same as the dollar change of the S&P 500. Therefore, the equation can be written as Eq. (7):

$$\begin{aligned}&\alpha^{*}[(\text{Dollar Difference of S\&P 500})/\text{Current S\&P 500}]\\ &\quad = \gamma^{*}\mathrm{RiskToleranceScore}.\end{aligned} \tag{7}$$

To make the equation match a regression form, the equation was rewritten as Eq. (8):

$$\begin{aligned}&\text{Current S\&P 500}\\ &\quad = (\alpha/\gamma)^{*}[(\text{Dollar Difference of S\&P 500})/\mathrm{RiskToleranceScore}]\end{aligned} \tag{8}$$

when α/γ is a reliable estimate. If the coefficient (i.e., α/γ) of [(Dollar Difference of S&P 500)/ RiskToleranceScore] shows statistical significance, then the coefficient implies that the risk tolerance score (from the scale) is associated with the utility function.

A time series analysis (see the function below) was used to evaluate Eq. (9):

$$Y(\text{S\&P 500}) = Constant + \beta_1^*(DollorDifference/RiskToleranceScore) + \beta_i^*(OtherControlVars.) + error \tag{9}$$

where, Y(S&P 500) denotes the current S&P 500; β_1 is the coefficient (i.e., α/γ in Eq. (4)) of the ratio between the dollar difference and the risk tolerance score; and βi is the sum of the coefficients for other control variables.

4. Data, methodology, and variables

This study used data obtained from a cross-sectional data-gathering project facilitated by the Rutgers New Jersey Agricultural Experiment Station where data were collected. The website, which was similar to one hosted by the University of Missouri (http://pfp.missouri.edu/research_IRTA.html) allowed consumers to access the Grable–Lytton risk tolerance scale. For the purposes of this study, data from 2008 to 2013 were analyzed. The sample frame from this period consisted of 169,280 individuals.

In the study, the total sample was divided into 10 sub-samples. The total sample, with 169,280 observations, was too large to analyze in an efficient manner. While a larger sample size increases statistical power (Ellis, 2010), the use of a very large sample means that even a small variance within a factor can result in a significant outcome, even though the factor may not have a meaningful effect (Lanz, 2012). In order to add make the analysis more robust, ten random samples were drawn from the total sample so that the model could be validated using repeated processes. Specifically, ten 10% samples were randomly selected without duplication across the samples. Additionally, these samples were delimited to include only respondents older than age 25 as a way to focus on those who would realistically be making investment decisions. As a result, the 10 samples had the following number of respondents: 8608 in random sample 1, 8023 in random sample 2, 8099 in random sample 3, 7961 in random sample 4, 8054 in random sample 5, 7929 in random sample 6, 7996 in random sample 7, 7934 in random sample 8, 7887 in random sample 9, and 7986 in random sample 10. The cross-sectional data were transformed to time-series data using the daily mean value of selected variables.

Because the S&P 500 is a representative stock index of the general stock market (Madura, 2014), the current S&P 500 index was used as the outcome variable in the model. Fig. 1 shows the S&P 500 index changes between 2008 and 2013. The figure shows the daily changes in the S&P 500 index price based on the closing data price. As explained above, the ratio between daily dollar changes in the S&P 500 and risk tolerance scores was used to estimate the coefficient (α/γ) in Eq. (8). The ratio was utilized as the main test variable in the methodology. Finally, four demographic variables were controlled in the analytic model: age, gender, education, and income. The choice of these variables was made based on two factors. First, these variables are known to be associated with risk taking attitudes and behavior (Hallahan et al., 2004), and second, these were the variables available in the dataset.

5. Result

Tables 1 and 2 show the coefficients of the ratio between dollar change in the S&P 500 and risk tolerance scores when the market return was positive (i.e., dollar change >0). Tables 3 and 4 show the coefficients of the ratio between dollar change in the S&P 500 and risk tolerance scores when the market return was negative (i.e., dollar change <0). As shown in Tables 1 and 2, the coefficients consistently and significantly had the same direction in each of the 10 models. In addition, the range of the coefficients was relatively reliable, ranging from −78.3 to −110.5, with most around -100.0. The consistent negative value from the 10 sampling models indicates that α has a negative value (see Eq. (5)). Referring back to the risk tolerance utility functions (see Eqs. (1), (2), and (5)), it is apparent that the economic utility functions match the risk tolerance scores.

As shown in Tables 3 and 4, the coefficients of the ratio were consistently and significantly the same in the samples. In addition, the range of the coefficients was relatively reliable, ranging from 119.8 to 145.2, with most around 130.0. The consistent positive value from each of the models indicates that α had a positive value (see Eq. (5)). Again, this provides evidence that the utility functions (see Eqs. (1), (2), and (5)), matched well with the economic utility function of risk tolerance. In addition, as shown In Table 5, the variance inflation factor (VIF) for each of the variables and models was less than 4.0, suggesting a low likelihood of multicollinearity among the variables.

6. Conclusion

The results from this study indicate that significant and consistent relationships were present in the data. The directional coefficients (α/γ) were similar across the different models. This implies that there is a clear and strong association between the economic utility function presented in this paper (i.e., objective market measure) and risk tolerance scores (i.e., subjective risk tolerance assessments). In addition, the range of coefficients (from −78.0 to −110.0) can be used to calculate the S&P 500 index by using the dollar change in the S&P 500 and risk tolerance scores (see Eq. (8)). In other words, it is possible to forecast the current value of the S&P 500 when the dollar change in the S&P 500 and investors' risk tolerance is also known.

On the other hand, the reverse of Eq. (8) can be used to forecast risk tolerance scores using the current value of the S&P 500 and the dollar change of the S&P 500. Eq. (8) can be rewritten as Eq. (10):

$$RiskToleranceScore = (\alpha/\gamma) * [(\text{Dollar Difference of S\&P 500})/\text{Current S\&P 500}] \ldots. \tag{10}$$

A specific element of Eq. (10) (i.e., [(Dollar Difference of S&P 500)/Current S&P 500]) can be interpreted as the percentage change in the S&P 500. As such, the percentage change in the S&P 500 index can be used to forecast the risk tolerance scores of investors (using Eq. (10)). For instance, when the market is down, say, by 5%, the change in the S&P 500 index can be multiplied by 130.0 so that risk tolerance can be expected to increase .65 points. On the other hand, when the market is up, say again by 5%, the change in the S&P 500 index can be multiplied by −100.0 so that risk tolerance scores can be expected to decrease .50 points.

The results from this analysis add to the literature by showing investments in the stock market are strongly associated with the risk attitudes and preferences of market participants. Subjectively measured risk tolerance scores can be used to forecast the value of the S&P 500 when S&P 500 change data is available. Conversely, the value of the S&P 500 can be estimated if risk tolerance scores in the aggregate are known. As a financial management tool, data from the S&P 500 can help a financial adviser anticipate the level of risk clients will be willing to take when investing. An increase in the S&P 500 should result in a decrease in risk tolerance, whereas a decrease in the index should increase willingness.

Results from this study should be evaluated in the context of certain limitations. The number of demographic variables used in the models was limited to those available in the dataset. It is

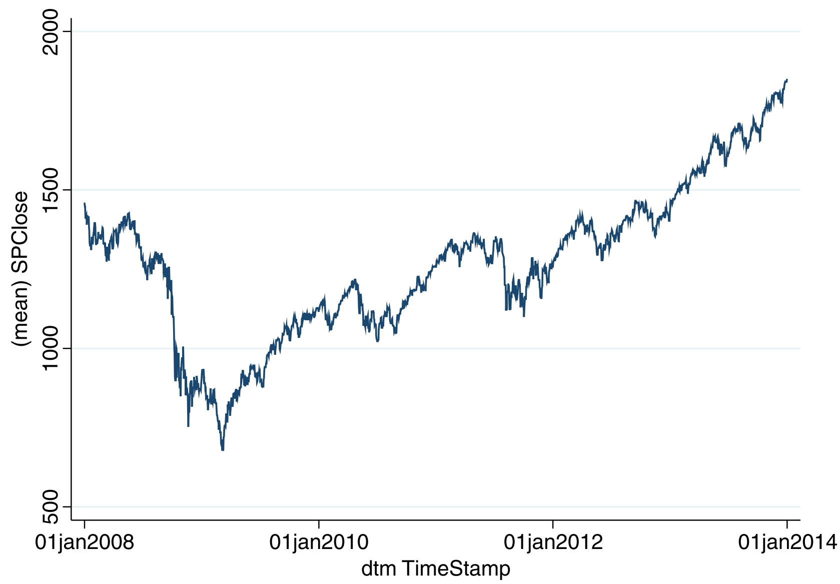

Fig. 1. Time series graph of S&P 500 prices (i.e., Close price) between 2008 and 2013.

Table 1
Time series analysis when the market is positive: Random samples 1 to 5.

	Random 1 coefficients	Random 2 coefficients	Random 3 coefficients	Random 4 coefficients	Random 5 coefficients
Ratio DC/RT	−94.13***	−103.24***	−78.26***	−102.90***	−94.17***
Gender	−62.49*	−.17	−38.90	40.13	−50.42
Age	−22.84*	−14.72	−30.18**	−18.30	−8.94
Education	−5.84	14.26	9.37	10.64	9.38
Income	2.52	−4.38	−9.20	−23.26*	−5.87
Constant	1468.20***	1344.19***	1447.25***	1411.919***	1375.67***
Adj. R^2	.04	.03	.03	.04	.03
F	6.46	5.03***	5.81***	7.26***	4.90***
Obs. (Days)	734	734	720	742	736

Table 2
Time series analysis when the market is positive: Random samples 6 to 10.

	Random 6 coefficients	Random 7 coefficients	Random 8 coefficients	Random 9 coefficients	Random 10 coefficients
Ratio DC/RT	−104.81***	−110.50***	−110.25***	−95.18***	−98.62***
Gender	5.95	16.62	7.20	−31.07	4.84
Age	−26.80*	−24.98*	−36.13***	−17.76	−12.11
Education	1.72	2.93	−12.95	5.56	−17.75
Income	6.74	−10.72	14.63	−5.75	5.46
Constant	1394.84***	1440.69***	1471.69***	1407.09***	1445.63***
Adj. R^2	.03	.04	.04	.03	.03
F	5.97	6.87***	7.82***	5.56***	5.62***
Obs. (Days)	767	766	752	731	741

Table 3
Time series analysis when the market is down: Random samples 1 to 5.

	Random 1 coefficients	Random 2 coefficients	Random 3 coefficients	Random 4 coefficients	Random 5 coefficients
Ratio DC/RT	139.59***	122.22***	131.11***	123.68***	134.79***
Gender	−96.60**	−2.92	37.66	−1.36	−58.61
Age	−39.87***	−14.56	−20.72	−30.74	−19.72
Education	16.55	7.69	12.94	2.36**	3.56
Income	−11.03	−13.29	2.79	4.33	7.59
Constant	1494.31***	1405.84***	1328.93***	1415.60***	1409.63***
Adj. R^2	.11	.06	.08	.07	.07
F	16.02	9.06***	10.89***	9.98***	10.56
Obs. (Days)	627	620	600	611	605

possible that omitted variables may have had an effect on the results. Second, the notion that risk tolerance may be useful in forecasting changes in the S&P 500 Eq. (7) should be evaluated as exploratory. Theoretically, the pathway is most likely from the S&P 500 to risk tolerance. Additional research is needed to test the causality of the associations.

Table 4
Time series analysis when the market is down: Random samples 6 to 10.

	Random 6 coefficients	Random 7 coefficients	Random 8 coefficients	Random 9 coefficients	Random 10 coefficients
Ratio DC/RT	126.46***	131.75***	145.20***	130.70***	119.79***
Gender	−30.27	25.90	−31.17	.23	−5.90
Age	−16.39	−11.56	−22.09	−26.51	−15.81
Education	13.65	.56	3.01	−7.43	−4.02
Income	−3.22	−22.97*	−16.89	−16.78	−8.71
Constant	1360.62***	1442.415***	1483.90***	1520.37***	1453.94***
Adj. R^2	.07	.07	.09	.09	.06
F	9.50	10.66***	12.06***	11.84***	9.27***
Obs. (Days)	610	626	620	621	620

Table 5
VIF values of variables in all models.

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10
Up Turn										
DC/RT	1.01	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.02
Gender	1.02	1.03	1.01	1.03	1.02	1.03	1.03	1.02	1.02	1.05
Age	1.11	1.14	1.08	1.09	1.21	1.13	1.08	1.10	1.11	1.12
Education	1.10	1.05	1.07	1.09	1.12	1.13	1.07	1.08	1.11	1.12
Income	1.23	1.23	1.14	1.16	1.31	1.25	1.18	1.17	1.22	1.27
Avg. VIF	1.09	1.08	1.06	1.08	1.14	1.11	1.07	1.08	1.09	1.12
Down Turn										
DC/RT	1.00	1.01	1.01	1.01	1.02	1.00	1.01	1.01	1.01	1.01
Gender	1.03	1.02	1.02	1.02	1.02	1.01	1.04	1.02	1.02	1.03
Age	1.08	1.11	1.09	1.10	1.09	1.10	1.09	1.10	1.06	1.11
Education	1.06	1.10	1.06	1.10	1.07	1.08	1.09	1.07	1.05	1.09
Income	1.17	1.20	1.17	1.19	1.16	1.18	1.19	1.20	1.11	1.22
Avg. VIF	1.07	1.09	1.07	1.08	1.07	1.07	1.08	1.08	1.05	1.09

References

Abdellaoui, M., Bleichrodt, H., L'Haridon, O., van Dolder, D., 2017. Measuring loss aversion under ambiguity: A method to make prospect theory completely observable. J. Risk Uncertain. 51 (1), 1–20.

Amuedo-Dorantes, C., Pozo, S., 2002. Precautionary saving by young immigrants and young native-born residents. South. Econ. J. 69 (1), 48–71.

Anderson, A., Dreber, A., Vestman, R., 2015. Risk taking, behavioral biases and genes: Results from 149 active investors. J. Behav. Exp. Finance 6, 93–100.

Bailey, J., Kinerson, C., 2005. Regret avoidance and risk tolerance. Financial Couns. Plan. 16 (1), 23–28.

Bali, T.G., Zhou, H., 2017. Risk, uncertainty, expected return. J. Financial Quant. Anal. 51 (3), 707–735. http://dx.doi.org/10.1017/S0022109016000417.

Barsky, R.B., Kimball, M., Juster, F.T., Shapiro, M., 1997. Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. Q. J. Econ. 112, 537–579.

Benartzi, S., Thaler, R.H., 2007. Heuristics and biases in retirement saving behavior. J. Econ. Perspect. 21 (3), 81–104.

Bodie, Z., Kane, A., Marcus, A.J., 2010. Essentials of Investments, eighth ed. McGraw-Hill/Irwin, New York, NY.

Chao, H., Ho, C.Y., Qin, X., 2017. Risk taking after absolute and relative wealth changes: The role of reference point adaptation. J. Risk Uncertain. 54 (2), 157–186.

Ellis, P.D., 2010. The Essential Guide to Effect Sizes: An Introduction to Statistical Power, Meta-Analysis and the Interpretation of Research Results. Cambridge University Press, UK.

Grable, J.E., 2000. Financial risk tolerance and additional factors that affect risk taking in everyday money matters. J. Bus. Psychol. 14 (4), 625–630.

Grable, J.E., Lytton, R.H., 1999. Financial risk tolerance revisited: The development of a risk assessment instrument. Financial Serv. Rev. 8 (3), 163–181.

Grable, J.E., Lytton, R.H., 2001. Assessing the concurrent validity of the SCF risk tolerance question. Financial Couns. Plan. 12 (2), 43–54.

Grable, J.E., Lytton, R.H., 2003. The development of a risk assessment instrument: A follow-up study. Financial Serv. Rev. 12 (3), 257–274.

Hallahan, T.A., Faff, R.W., McKenzie, M.D., 2004. An empirical investigation of personal financial tolerance. Financial Serv. Rev. 13, 57–78.

Hanna, S., Chen, P., 1997. Subjective and objective risk tolerance: Implications for optimal portfolios. J. Financial Couns. Plan. 8 (2), 17–26.

Hoffmann, A.O.I., Post, T., Pennings, J. M.E., 2013. Individual investor perceptions and behavior during the financial crisis. J. Bank. Finance 37 (1), 60–74.

Holzmeister, F., 2017. oTree: Ready-made apps for risk preference elicitation methods. J. Behav. Exp. Finance 16, 33–38.

Kamstra, M.J., Kramer, L.A., Levi, M.D., Wermers, R., 2017. Seasonal asset allocation: Evidence from mutual fund flows. J. Financial Quant. Anal. 52 (1), 71–109. http://dx.doi.org/10.1017/S002210901600082X.

Kirchler, M., Andersson, D., Bonn, C., Johannesson, M., Sørensen, E.Ø., Stefan, M., Tinghög, G., Västfjäll, D., 2017. The effect of fast and slow decisions on risk taking. J. Risk Uncertain. 54 (1), 37–59.

Kumari, J., Mahakud, J., 2015. Does investor sentiment predict the asset volatility? Evidence from emerging stock market India. J. Behav. Exp. Finance 8, 25–39.

Kuzniak, S., Rabbani, A., Heo, W., Ruiz-Menjivar, J., Grable, J.E., 2015. The Grable and Lytton risk-tolerance scale: A 15-year retrospective. Financial Serv. Rev. 24 (2), 177–192.

Lanz, B., 2012. The large sample size fallacy. Scand. J. Caring Sci. 27 (2), 487–492.

Lusardi, A., 1998. On the importance of the precautionary saving motive. Am. Econ. Rev.: Am. Econ. Assoc. Pap. Proc. 88, 449–454.

Madura, J., 2014. Personal Finance, fifth ed. Pearson Education, Upper Saddle River, NJ.

Markowitz, H., 1952. Portfolio selection. J. Finance 7, 77–91.

Michaelides, A., Zhang, Y., 2017. Stock market mean reversion and portfolio choice over the life cycle. J. Financial Quant. Anal. 52 (3), 1183–1209. http://dx.doi.org/10.1017/S0022109017000357.

Roszkowski, M.J., Davey, G., Grable, J.E., 2005. Insights from psychology and psychometrics on measuring risk tolerance. J. Financial Plan. 18 (4), 66–71.

Ryack, K.N., Kraten, M., Sheikh, A., 2016. Incorporating financial risk tolerance research into the financial planning process. J. Financial Plan. 29 (10), 51–61.

Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. J. Risk Uncertain. 5 (4), 297–323.

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Declaration of Competing Interest statements were not included in the published version of the following articles that appeared in previous issues of "Journal of Behavioral and Experimental Finance".

The appropriate Declaration/Competing Interest statements, provided by the Authors, are included below.

(1) "Wash trades as a stock market manipulation tool" [Journal of Behavioral and Experimental Finance, 2018; 20C: 92–98] https://doi.org/10.1016/j.jbef.2018.08.004.
Declaration of competing interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

(2) "Stop the music? The effect of music on risky financial decisions: An experimental study" [Journal of Behavioral and Experimental Finance, 2019; 24C: 100231] https://doi.org/10.1016/j.jbef.2019.07.003.
Declaration of competing interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

(3) "A test of the relevant association between utility theory and subjective risk tolerance: Introducing the Profit-to-Willingness ratio" [Journal of Behavioral and Experimental Finance, 2018; 19C: 84–88] https://doi.org/10.1016/j.jbef.2018.05.003.
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(4) "Understanding the impact of severe hyperinflation experience on current household investment behavior" [Journal of Behavioral and Experimental Finance, 2018; 17C: 60–67] https://doi.org/10.1016/j.jbef.2017.12.008.
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(5) "The limits of social identity impact on economic preferences" [Journal of Behavioral and Experimental Finance, 2019; 24C: 100239] https://doi.org/10.1016/j.jbef.2019.100239.
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(6) "Perception of intentionality in investor attitudes towards financial risks" [Journal of Behavioral and Experimental Finance, 2018; 23C: 189–197] https://doi.org/10.1016/j.jbef.2017.12.011.
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(7) "Ready-made oTree apps for time preference elicitation methods" [Journal of Behavioral and Experimental Finance, 2019; 23C: 23–28] https://doi.org/10.1016/j.jbef.2019.04.011.
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(8) "How does corruption undermine banking stability? A threshold nonlinear framework" [Journal of Behavioral and Experimental Finance, 2020; 27C: 100365] https://doi.org/10.1016/j.jbef.2020.100365.

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(9) "Domain-specific risk-taking among finance professionals" [Journal of Behavioral and Experimental Finance, 2020; 27C: 100331] https://doi.org/10.1016/j.jbef.2020.100331
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(10) "This time is indeed different: A study on global market reactions to public health crisis" [Journal of Behavioral and Experimental Finance, 2020; 27C: 100349] https://doi.org/10.1016/j.jbef.2020.100349.
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(11) "Behavioral insights on business taxation: Evidence from two natural field experiments" [Journal of Behavioral and Experimental Finance, 2018; 18C: 30–49] https://doi.org/10.1016/j.jbef.2018.01.004.
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(12) "zBrac — A multilanguage tool for z-Tree" [Journal of Behavioral and Experimental Finance, 2019; 23C: 59–63] https://doi.org/10.1016/j.jbef.2019.04.006.
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(13) "Exponential growth bias matters: Evidence and implications for financial decision making of college students in the U.S.A." [Journal of Behavioral and Experimental Finance, 2018; 19C: 56–63] https://doi.org/10.1016/j.jbef.2018.04.002.
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(14) "t-Tree: The Tokyo toolbox for large-scale combinatorial auction experiments" [Journal of Behavioral and Experimental Finance, 2019; 24C: 100235] https://doi.org/10.1016/j.jbef.2019.100235.
Declaration of competing interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

(15) "Compulsory versus voluntary savings as an incentive mechanism in microfinance programs" [Journal of Behavioral and Experimental Finance, 2020; 26C: 100317] https://doi.org/10.1016/j.jbef.2020.100317.
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